

Improving Regression-Based Myoelectric Control: User Compliance, Simultaneity, and Incremental Learning

by

Christian Morrell

Bachelor of Science in Electrical Engineering, UNB, 2022

A Thesis Submitted in Partial Fulfilment of
the Requirements for the Degree of

Master of Science in Engineering

In the Graduate Academic Unit of Electrical and Computer Engineering

Supervisor: Erik Scheme, PhD,
Electrical and Computer Engineering

Examining Board: Brent Petersen, PhD,
Electrical and Computer Engineering, Chair
Kevin Englehart, PhD,
Electrical and Computer Engineering
Scott Bateman, PhD,
Computer Science

This thesis is accepted by the
Dean of Graduate Studies

THE UNIVERSITY OF NEW BRUNSWICK

March, 2025

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Abstract

Regression-based myoelectric control offers the potential for simultaneous, independent, proportional control, but current implementations are limited by inconsistent training protocols and robustness issues. This thesis aims to address these limitations by providing a novel training protocol that overcomes key robustness issues that have hindered regression-based myoelectric controllers for decades. Two studies are performed, one demonstrating the volatility of current training protocols and the other proposing an alternative paradigm leveraging context-informed incremental learning. Results first show that models trained using existing protocols are affected by simply changing the visual prompting style. In response, the novel training paradigm is shown to significantly improve performance compared to traditional approaches. Furthermore, multiple co-adaptive approaches are contrasted to demonstrate the importance of building tolerance to user behaviours into myoelectric controllers. The results presented in this work provide important considerations for training myoelectric controllers and emphasize the value of designing with the user in mind.

Dedication

To my parents, Wyatt and Tammy; my sister, Ashtyn; and my fiancée, Jianna.

Acknowledgements

First and foremost, I'd like to extend my heartfelt thanks to Dr. Erik Scheme for being a phenomenal advisor, guide, and friend throughout this process. Your unwavering commitment to your students is noticed and appreciated by all under your supervision. More than anything, I appreciate that I was always treated like I could teach you something, and was often encouraged to do so. Without a doubt, it is thanks to you that my time as a graduate student developed me as a person instead of just as a student. Next, thank you to Evan Campbell and Ethan Eddy for providing me with mentorship, guidance, and laughs as I learned. Taking the time out of busy schedules to help other students is not easy, but these two do it exceptionally well—much better than they play NHL 18, if I might add. Nevertheless, none of this work would be possible without the guidance of these three, all of whom are a joy to work with and be around. It is thanks to these positive relationships and supervision that I found such joy in research, which I believe I will carry with me for the rest of my life.

Although academic supervision is important, I have learned that keeping myself sane is also an important (and often overlooked) aspect of productivity. To that I primarily attribute to Jianna for her patience as I worked late and filled my free time with sports to deal with stress. Your flexibility, including scorekeeping my awful men's league hockey games just to see me, is the only reason that I could

balance all of these aspects of my life. More than anything, I am excited to do life with you. Thank you to my parents, Wyatt and Tammy, for always supporting me, encouraging me, and being an example of the important things in life. Thank you to Ashtyn for being an inspiration to me by balancing work, school, and getting ready for a baby all at once. Last but not least, thank you to everyone I crossed paths with at the IBME. Whether it be quick conversations in the hall, lunchtime discussions, or collaborating on projects, everyone I encountered made it a bit easier to get through the day—and for that, I thank you.

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Chapter 1

Introduction

1.1 Motivation

Myoelectric control, the use of electromyography (EMG) signals as a control source, has been researched for decades [2–4]. Although it is most commonly used to enable individuals with limb difference to control a powered prosthesis [4, 5], modern myoelectric control has emerging applications in rehabilitation engineering, human-robot interaction, teleoperation, and general ubiquitous computing [6–10]. These broader applications of myoelectric control have shown to be promising in many areas, from more convenient user interfaces [11] to improved rehabilitation outcomes [12, 13]. Despite its increased adoption and exploration, the functionality of current myoelectric prostheses remains limited, in part due to limitations with their control schemes [3, 14]. While classification-based pattern recognition control—the state-of-the-art in commercial prosthetics (e.g., Coapt, LLC)—has moved the field forward, it requires that users move each degree of freedom under control sequentially (e.g., first rotating the wrist, then closing the hand). This is in stark contrast to natural human movement which comprises sophisticated and simultaneous coordination be-

tween the hand and the wrist. This difference highlights a fundamental disconnect between the end goal of a prosthesis and the current state-of-the-art. More akin to the natural movement of a human limb, researchers have claimed that regression-based control offers the promise of simultaneous, independent, proportional control of multiple degrees of freedom (DoFs), but robustness issues and increased training burden remain critical challenges [14–17].

Although regression-based myoelectric control has been researched for over a decade [15, 18–20], model training remains confounded by somewhat naive assumptions about user compliance and a lack of standardized training protocol. In classification-based approaches, data are collected for machine learning while end-users elicit a series of discrete motion classes (e.g., hand open) for a set period of time. In proportional control, the intensity of the contraction is used to control the velocity of the device, but this is largely considered independent of model training [21]. Conversely, regression-based control expressly merges intent derivation and proportional control by assigning a continuous value to the activation level of a DoF (e.g., a value between $[-1, 1]$ for wrist rotation, where -1 is full pronation, 0 is rest, and 1 is full supination). While this enables simultaneous proportional control, it requires the user to provide quality data throughout the full range and permutations of possible outputs to inform model training. While a variety of methods have been explored to enable the collection of quality training data for regression-based systems [19, 20, 22], researchers have often used visual prompts due to their accessibility and ease of use [15, 16, 23]. These visual prompts, wherein users are assumed to follow a cursor moving on a screen by modulating their contractions in agreement with the movement of the cursor, have their own challenges, though, and the literature lacks consistency of prompting methods and styles [15, 16, 24]. This disagreement extends to what data should be collected using this so-called screen-guided training (SGT), where some suggest that adding examples of simultaneous activations to the

training set helps [25,26] and others claim that it is not necessary [18,19,23]. Moreover, visual prompts assume that the user perfectly tracks the intended contraction strength over the repetition, which recent work has questioned, and discrepancies can substantially impact model learning and performance [27]. Physiological factors such as fatigue and contraction strength may also have an impact, as motor unit recruitment during these conditions can vary [28]. To make matters worse, these issues may be intertwined. That is, the chosen protocol—including the prompting style, the inclusion or exclusion of simultaneous combinations of motions, and the strength of the maximum contraction—likely influences how well users comply with ground truth labels, further confounding how they should train.

Many of the challenges associated with SGT approaches stem from the discrepancy between offline and online performance, largely because SGT data are not fully representative of real-time use [29]. Given that the online task includes the user as part of the loop, an alternative training approach called co-adaptation has been explored. This approach integrates the user in the loop during training, enabling both the user and the model to learn together. Since real-time information from the environment is essential during co-adaptation, many approaches use a virtual environment, a method frequently employed in myoelectric control [30], where model predictions move a cursor on a screen instead of controlling a physical prosthesis [23,31]. For example, in such virtual setups, the wrist flexion/extension DoF may correspond to left/right cursor movement [23]. While co-adaptation has shown promising performance when applied to regression-based myoelectric control [23,32,33], existing approaches make bold assumptions about the user’s compliance during training—such as the user consistently following the optimal path [31]. Furthermore, in order to prompt different intensities, many applications of co-adaptation continue to use position-based mappings (mapping the intensity of the contraction to the position of the cursor), whereas commercial myoelectric prostheses use velocity control. This

disconnect may introduce differences in user behaviour between model training and subsequent use, potentially degrading some of the benefits of co-adaptation.

Ultimately, the lack of standardization of training protocols has led to uncertainty regarding the training of regression-based myoelectric control, contributing to unsolved robustness issues such as action interference (i.e., movement in an unintended DoF when the user tries to move another DoF in isolation) [15–17, 34–36] and drift (i.e., undesired cursor movement when the user tries to stay at rest) [15, 16, 34]. These two factors alone can make regression-based control unusable and degrade user and clinical confidence in its viability as a deployable solution for next-generation prosthetics.

The goal of this work was, therefore, to explore the impact of the training protocol on regression-based myoelectric control systems and provide a method to overcome these critical robustness issues. Preliminary work first showed that something as small as the visualization method used for prompting can influence user behaviours. Specifically, certain prompting styles appeared to amplify undesirable behaviours that were found to degrade performance for some models but not others, further demonstrating the wealth of confounds related to SGT. Moreover, another distinct behaviour introduced by differences in prompting method unexpectedly outperformed the baseline approach despite yielding worse compliance with the prompt. Interestingly, recent work by others [27] has shown similar interactions and complications. Others have shown that spatial alignment with the prompt (in terms of matching signal amplitude) has a greater impact than temporal alignment, but that this effect can vary significantly depending on the control algorithm and the amount of data [37]. Altogether, this body of evidence draws into question whether improving user compliance with SGT-based prompting methods is the answer to outstanding challenges in regression-based control.

Consequently, building on the success of co-adaptive approaches in regression-based myoelectric control [23, 38], this work explores a new paradigm called context-informed incremental learning (CIIL) in a regression environment for the first time. CIIL has recently been shown to significantly improve classification-based control by incorporating context from a goal-oriented task environment to incrementally train the model, thus incorporating user-in-the-loop control behaviours [29, 39, 40]. Two novel co-adaptive approaches inspired by CIIL are compared against different SGT approaches to investigate the effect of adding simultaneous motions to the training set, implementing co-adaptation, and modifying the co-adaptive protocol to enable better resilience to differences in user behaviours.

The performance of these models was evaluated in a Fitts’ Law-inspired target acquisition test and described by a suite of metrics, including throughput—a measure of information bandwidth of a control channel [1, 30]. Additionally, two important metrics are introduced to better describe the performance in two key challenges in regression control; *action interference* and *drift*. This work provides important insights into the limitations of existing SGT-based regression training and suggests that user-centered adapting training may be a viable new approach to advancing this promising control paradigm.

1.2 Background

Early implementations of myoelectric control used simple dual-site control, often called conventional control. In this approach, a pair of electrode sites are placed over antagonist muscles, and the difference in contraction intensity is mapped to a function of the prosthesis [2]. Although functional, dual-site control struggles to reliably control more than one function without the use of counterintuitive measures like mode switching [2, 41]. Today, state-of-the-art pattern recognition systems employ

classification-based control schemes, where multiple EMG signals are used as input to a machine learning classifier and the output decisions are mapped to a variety of different prosthesis functions [41].

To facilitate this process, EMG signals are acquired via electrodes placed over muscles of interest that detect the electrical activity of the underlying motor units [42]. Typically, recorded EMG signals are then filtered with a band-pass filter ($f_c = 20, 450 \text{ Hz}$) to remove motion artifact and avoid aliasing and a notch filter ($f_c = 60 \text{ Hz}$) to remove power line interference [5]. Filtered EMG signals are then enframed with a specified window size (typically in the order of 100-200 ms) and increment (typically in the order of 25-50 ms) to approximate a stationary view of the signal [41, 43]. Next, raw windows or features extracted from the windows are passed to a machine learning model for classification, which moves the corresponding function of the prosthesis [41]. Classifiers can also be augmented with proportional control, where the magnitude of the signal (such as the mean absolute value of the window) can be used to modulate the speed of the cursor based on the strength of the contraction [21].

Whereas classification-based control predicts a discrete motion class (selecting 1 of N possible actions, defined during training), regression-based control predicts a continuous output along a DoF (see Figure 1.1). For example, a regressor trained to predict wrist rotation may assign -1 to maximum pronation and +1 to maximum supination. Regression-based control, therefore, offers two main potential advantages over classification-based control: 1) proportional control is inherently factored into the output, removing the need for post hoc proportional control with heuristically chosen hyperparameters [21], and 2) it enables the simultaneous, independent control of multiple DoFs—potentially even without explicitly collecting simultaneous motions in the training set. The ability for simultaneous, independent, proportional control offers the promise of more natural control and has been shown to improve performance in constrained functional tasks [36, 44–47]. However, regression-based

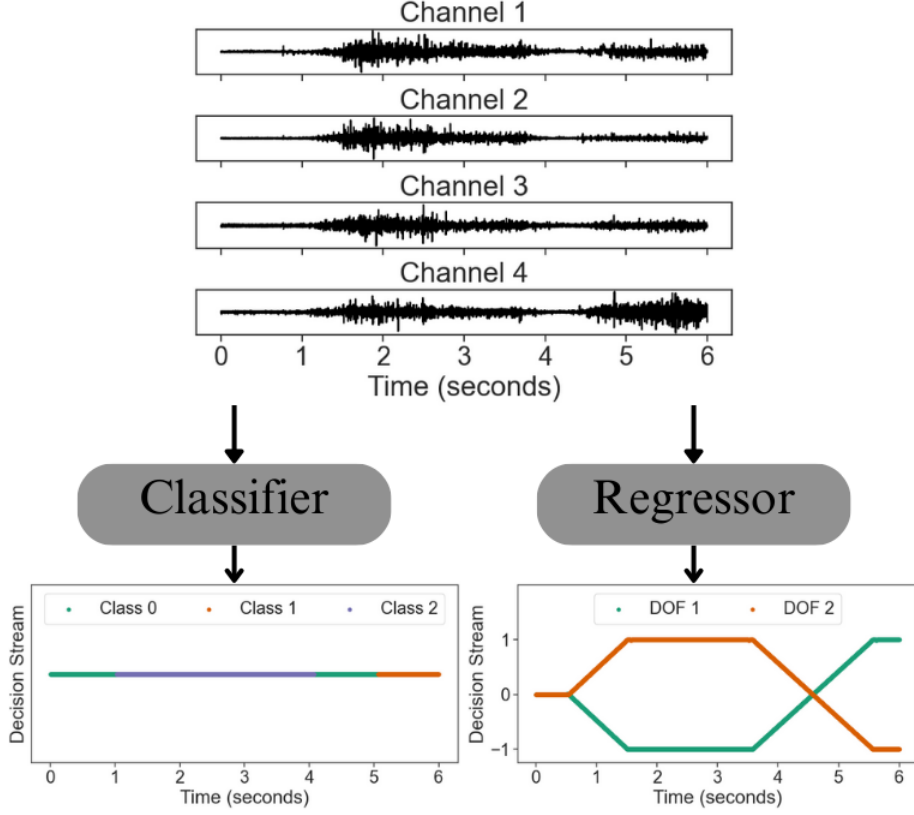


Figure 1.1: Comparison of classification and regression applied to myoelectric control.

control is still limited by three important issues—*training*, *action interference*, and *drift*—as explained in the following sections.

1.2.1 Training

To facilitate any machine learning-based myoelectric control, data must first be acquired from which models can be trained. Providing these training data for regression-based myoelectric control systems is particularly complicated given the need to obtain labelled data across various contractions and intensities. Furthermore, there are a variety of methods used throughout the literature to obtain these labels with no apparent standard. Earlier works using regression-based myoelectric control primarily used either force [20, 48] or position [18–20] mappings to label EMG data via force transducers or computer vision tracking, respectively. These approaches

are still popular today, with works using inexpensive infrared cameras [27, 49], more complex multi-camera computer vision systems [9, 50], custom force transducers [51], or data gloves [50, 52] to acquire ground truth labels. To make these approaches viable for users with a limb difference, mirror training (i.e., contra-lateral training) must be used, where EMG data and ground truth labels are recorded from the opposite, in-tact, limb [27, 49]. While mirror training has been successful in previous works [27, 49], it requires the user to faithfully elicit contractions bilaterally and cannot be used by persons with bilateral limb difference, limiting its clinical applicability. Regardless of mirror training or not, both position and force mappings themselves require additional instrumentation. Computer vision systems, for example, require extra setup and are susceptible to noise, lighting conditions, and privacy concerns [53]. Additionally, they only track limb position, whereas EMG is more representative of force, leading to challenges in user compliance and reducing the correlation between the acquired signal to the training target. Similarly, force-based mappings often require custom hardware to fit a specific set of gestures (e.g., measuring finger forces [54]) or expensive commercial solutions (e.g., data glove [52]), often constraining the possible DoFs that can be measured.

These limitations have led researchers to use screen-guided prompting for training regression-based myoelectric control because it does not require any external hardware, can be mapped to position or velocity-based control, and are viable for users with a bilateral limb difference [15, 16, 24, 27, 34]. When using visual prompting (i.e., mimic training [27]), participants are shown an animation on a screen and asked to map the strength of their contraction to a changing signal in real time. For example, participants may be shown a rising and falling bar [16], a point moving along a Cartesian plane [15], a visualization of the DoF amplitude over time [24, 34], or an anthropomorphic visualization [27]. Despite the benefits of visual prompts, however, training protocols lack consistency across studies in terms of prompting style and

repetition structure. The use of these visual prompts as labels for machine learning also assumes that the user accurately tracks the signal shown in real-time (i.e., user compliance), which is limited due to reaction time and the user’s ability to accurately modulate their contraction strength [26,37]. To wit, Tully et al. [27] recently showed that mirror training provides more accurate labels than mimic training (because the matching is driven by bilateral symmetry rather than a prompt and response). They also showed that this discrepancy can have significant impacts on usability.

Outside of the prompting method itself, the type of data collected can drastically impact performance [26,34,55]. For example, factors such as the inclusion of the transient phase [55] or variations in hold time duration [56] can have a substantial effect. The potential inclusion of simultaneous (i.e., multi-DoF) motions has also led to confusion throughout the field, beyond the increased training burden that comes with collecting the various permutations of DoFs and intensities. While some studies suggest that simultaneous motions are unnecessary in the initial calibration data (assuming that the combined activation of DoFs can be inferred from individual DoF training data alone) [18,19,23], others have shown that their inclusion has benefits [25,26], whereas others have argued that including them could even harm the performance of isolated movements [34]. The type of data collected during training likely has an impact on user compliance as well, further complicating training. In particular, user compliance with the prompt may be influenced by the speed of transitions, the length of sustained contractions, and whether simultaneous motions are being performed, making it difficult to determine optimal training strategies. For this reason, researchers have employed a diverse range of training protocols throughout the regression-based myoelectric control literature, limiting the generalizability and pace of existing research.

1.2.2 Action Interference

A well-documented limitation of existing regression-based myoelectric control systems is the undesired activation of other DoFs while trying to perform single-DoF movements [15–17, 34–36]. While simultaneity may be beneficial, it must be controllable by the user to be effective. Ameri et al. [15, 16] confirmed this by controlling a cursor in a Fitts’ Law task, demonstrating that while high-amplitude predictions are important for speed—and by extension, throughput—low-amplitude performance is more impactful on control metrics such as path efficiency and overshoots. This observation is attributed to the concurrent activation of unintended DoFs, which Ameri et al. suggest causes frustration, lower efficiency, and degrades control performance across all metrics [15, 16]. To complicate matters further, Smith et al. [34] suggested, based on offline results, that adding simultaneous motions to the training set improved overall performance, but hurt performance for isolated motions.

While this phenomenon has been alluded to in many works, Nowak et al. [17] were the first to term it *action interference* in a comparison of force myography and EMG. Specifically, Nowak et al. [17] argued that action interference is the primary reason force myography outperformed EMG in their experiment, attributing it to the way EMG features are clustered, which causes some actions to lie close to the cluster associated with no motion and trigger unintentional activations. Others have since reported this phenomenon in laboratory settings, where Zhu et al. [36] found that sequential control was better for a box and blocks task, which is primarily single-DoF movements, but simultaneous control was better for clothespin relocation and doorknob tasks, which benefit from multi-DoF movements. Unlike the most appropriate training visualization method, there is a strong consensus that action interference is an ongoing issue hindering regression-based myoelectric control [15–17, 34–36].

1.2.3 Drift

Similar to action interference, regression-based myoelectric controllers have been shown to perform poorly at the low end of proportional control, both when moving in isolation and when trying to remain at rest (i.e., cursor drift when the user intends to stop) [15, 16, 34]. Classification-based control has the benefit of class boundaries, where the intra-class variance provides some margin for error while remaining in the correct class. Regression-based control lacks this robustness [57], however, manifesting as small, jittery movements when the model predicts small values rather than exactly 0 while the user is at rest, which we call *drift*.

The most common method for mitigating this drift is the use of a so-called *deadband*, where the output of the regressor is relabelled to 0 when it is below some activation threshold [15, 16, 27, 34, 47]. The non-linearity that this introduces in the proportional outputs has been addressed in multiple ways, including using a straight threshold with no remapping [36], remapping the outputs so that the user can still use the full range of values [15, 16, 27, 47], a velocity ramp [24], or some combination of a threshold and velocity ramp [34]. The magnitude of the activation threshold varies greatly throughout the field as well, with some studies setting a universal threshold [27, 34] and others setting it on a per-subject basis [36, 47]. Similar to the issues with training, many methods have been proposed to handle the drift encountered during piloting, yet no consensus exists on the best approach. For instance, whether the output is rescaled or not may impact low-end performance, which is known to be crucial [15, 16]. Just like training, the lack of standardization in activation thresholds and post-processing methods has unclear implications on performance, further hindering progress in regression-based myoelectric control.

1.3 Objectives

Given that these robustness issues have hindered regression-based myoelectric control for many years, the current approaches should be questioned. In particular, the lack of standardization regarding training has caused confusion among researchers and allowed issues such as action interference and drift to persist for decades. At least some of these issues likely arise because traditional SGT approaches make naive assumptions about user compliance and fail to capture user-in-the-loop behaviours, causing a disconnect between training and end-use. A new training paradigm capable of capturing these real-time behaviours has the potential to fix these robustness issues, avoid the confounds related to SGT, and provide a standard for regression-based myoelectric control moving forward.

Consequently, to address these recognized limitations in the training and performance of regression-based myoelectric control, this thesis comprises three strategic aims:

Specific Aim 1: Investigate whether users accurately follow screen-guided training prompts and examine the impact of prompting style on user compliance.

Specific Aim 2: Demonstrate the viability of regression-based CIIL as an alternative to traditional SGT.

Specific Aim 3: Explore the benefits of modifying traditional co-adaptive methods to tolerate user compliance issues.

1.4 Thesis Structure

This research explores regression-based myoelectric control, specifically in terms of how the training protocol can impact usability, simultaneity, and user experience.

This thesis consists of two experiments, each designed to address these specific aims: the first addresses Aim 1 and the second targets Aims 2 and 3. Each experiment, presented in its own chapter, is presented as a standalone article, providing the necessary motivation, background, methods, results, and discussion. Both studies are first presented individually, followed by a summary of the findings, limitations, and potential future directions described in Chapter 4. A brief introductory description of each study is provided below.

1.4.1 Experiment 1: Exploring User Compliance in the Training of Regression-Based Myoelectric Control

Chapter 2 describes a pilot experiment, where multiple training protocols were explored to determine their impact on usability [58]. This preliminary work targets Aim 1 and strongly motivates the rest of the work of this thesis. In the first portion of this work, participants were asked to perform mimic training using various different visual prompting styles. The temporal alignment between the mean absolute value and the prompted label over the course of each repetition was first investigated to identify how accurately the user tracked the prompt. Consequently, two distinct user behaviours were identified when comparing the data acquired using each prompting style, raising the question of the effect of these behaviours on downstream usability. A second sub-study was consequently conducted where users purposely emulated these behaviours during training before using the resulting models to perform a series of target acquisition tasks. Results suggest that these prompting-style-induced behaviours can deteriorate performance for some models. Unexpectedly, one of the behaviours actually improved online performance despite demonstrating worse temporal alignment with the prompt, suggesting that temporal alignment may not be impactful enough to fix known robustness issues with regression-based myoelectric

controllers. This article was published and presented at the 2024 Myoelectric Control Symposium [58].

1.4.2 Experiment 2: Context-Informed Incremental Learning Improves Throughput and Reduces Drift in Regression-Based Myoelectric Control

Motivated by the acknowledged limitations of existing regression-based myoelectric control training, this study—described in detail in Chapter 3—introduced a novel adaptive approach for training regression-based myoelectric control. The uncertainty of the impact of the numerous challenges associated with user compliance with visual prompting, their possible interactions, and the differences in user behaviours they induce motivated this exploration of an alternative. Consequently, a novel training paradigm was proposed to overcome the confounds introduced by SGT while also mitigating known robustness issues such as action interference and drift. CIIL was modified for use with regression, for the first time, and compared with traditional SGT approaches. The proposed approach yielded significant improvements across multiple metrics, and targeted modifications to the adaptive protocol were shown to further improve on specific robustness issues. Two novel metrics were proposed to better describe control in a regression-based velocity-controlled environment, specifically related to the use of simultaneity. This experiment targeted Aims 2 and 3 through extensive analysis of screen-guided training approaches, co-adaptation, user compliance, and the use of simultaneity. Because it comprises a different training paradigm, it also indirectly mitigated the challenges in Aim 1. This work is under review for publication in a Special Issue on User-Centered Innovations in Upper-Limb Prosthetics in the IEEE Transactions on Neural Systems and Rehabilitation Engineering.

Chapter 2

Exploring User Compliance in the Training of Regression-Based Myoelectric Control

2.1 Abstract

Regression-based myoelectric control is promising because it could enable simultaneous independent control over multiple degrees of freedom. However, limitations in the robustness of online control and the added complexity of acquiring labelled training data have hindered its adoption. The scattered mix of prompting methods, visualization styles, and speeds used in the literature to collect labelled regression training data has obfuscated how these different prompting styles may affect the performance of regression-based myoelectric control. This work thus begins to investigate the potential effects that different visualizations may have on user behaviours and the quality of acquired training data for myoelectric control. Two distinct behaviours, referred to as *all or nothing* and *anticipation*, emerged when comparing

the training data of three different prompting styles. Subsequently, 6 subjects were coached to emulate each of these behaviours during training and then completed a 10-trial Fitts’ Law to assess the online usability of two different support vector regression (SVR) models. Results show that both user behaviours and the choice of regression model can have profound impacts on the usability of regression-based myoelectric control. Notably, real-time performance was severely degraded by the *anticipation* behaviour when using a linear kernel SVR, resulting in a 70% reduction in completion rate. These preliminary results motivate future work into how best to prompt users when training for supervised regression-based myoelectric control.

2.2 Introduction

Despite high levels of abandonment, many commercial upper-limb prostheses still employ decades-old control strategies [14]. Sophisticated coordination between the hand and wrist is needed for advanced tasks, yet even current prosthetic devices rely on sequential control schemes [14]. Regression-based control offers the potential of simultaneous independent control, but questions about the robustness of online regression control (e.g., challenges with quiescence, drift, susceptibility to confounds) and the increased complexity of acquiring labelled training data remain [14, 15].

A variety of training protocols have been used to acquire training data for regression-based systems, ranging from the use of force transducers, to limb kinematics tracking, to purely visual prompting styles [15, 19, 20, 22]. Although the use of force and position mappings have been effective [20], they are not viable for users with upper limb differences, leading researchers to focus on visual prompts [15]. Unlike in classification tasks, however, the use of visual prompting in regression not only assumes that the user is performing the correct contraction, but also that they are tracking the amplitude of the degree of freedom closely over the entire progression. Given the

likelihood of deviations in compliance and timing, however, this may not always be the case, potentially resulting in a discrepancy between the elicited contractions and the ground truth labels used to train the model. Furthermore, a variety of prompting methods, visualization styles, and speeds have been used in the literature, without clarity about how they may affect user behaviours or model training, or what role they may have on the online usability of regression-based myoelectric control [15,19]. Consequently, this work describes an early exploration of the potential differences in user behaviours based on changes in prompting for regression-based myoelectric control.

2.3 Methods

2.3.1 Data Collection and Preparation

Eight subjects participated in this exploratory pilot work (5 male, 3 female, 22 - 31 years old) as approved by the University of New Brunswick’s Research Ethics Board (REB 2022-122). EMG data were collected from the forearm using the EMaGer cuff, a 64-channel high-density electromyography (HD-EMG) device comprised a stretchable 4 x 16 array of EMG electrodes [59]. LibEMG, an open-source Python library for processing EMG, was used to facilitate data streaming, the creation of visual prompts, and real-time myoelectric control [5]. EMG data were bandpass filtered from 20-450 Hz to remove motion artefacts and notch filtered at 60, 120, 240, and 360 Hz to remove power-line interference. The filtered signals were then normalized to unit variance and zero mean to improve visualizations and standardize data for model training. The EMG time series were then enframed using 250ms windows with 50ms overlap, from which the Hudgins’ Time Domain feature set were extracted [60].

2.3.2 Prompting Styles

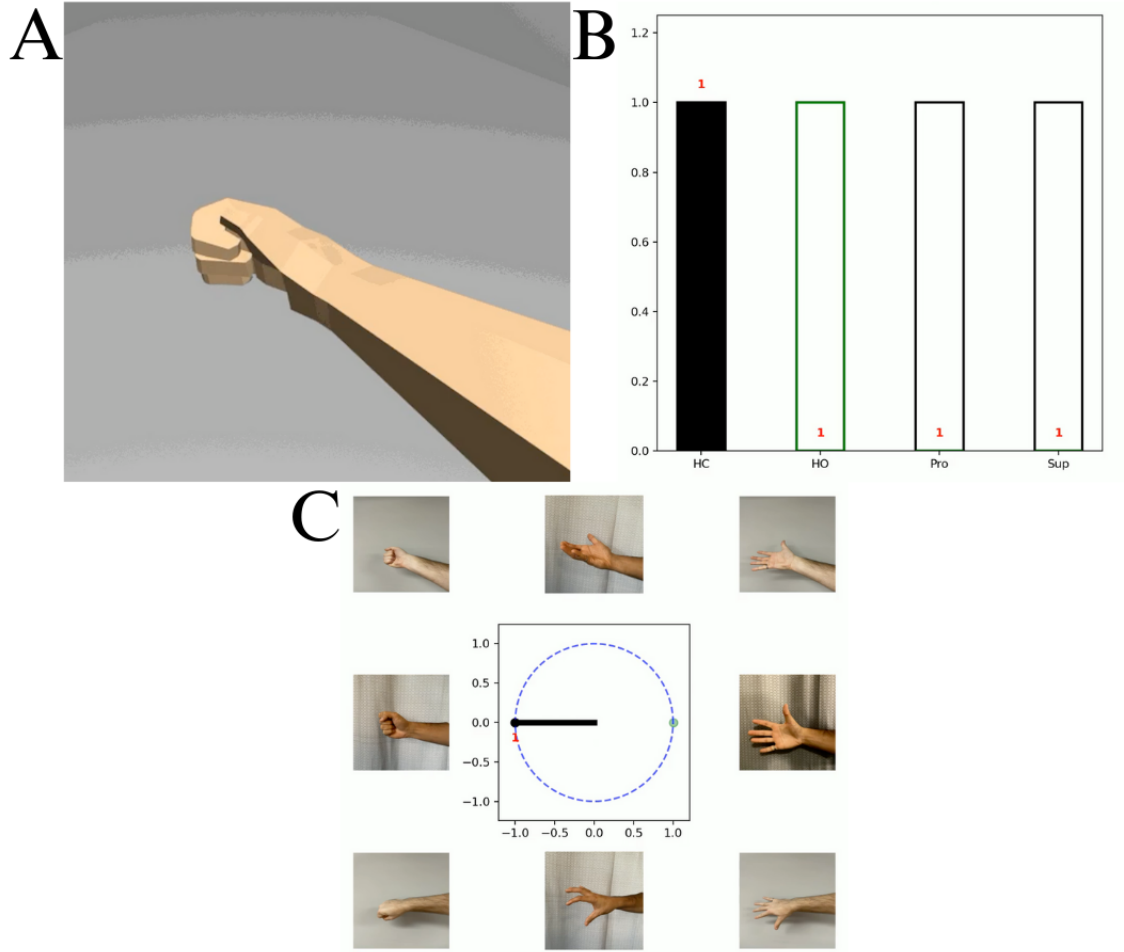


Figure 2.1: Example of the Anthropomorphic (A), Bar plot (B), and Cartesian (C) visualizations used for prompting the user during training. For the Bar plot and Cartesian visualizations, countdowns were shown in red during periods of constant amplitude and the next destination of the target was shown in green.

Three different prompting approaches were explored, based on their prevalence in the literature [19, 61, 62] and as distinct presentation styles. Contractions corresponding to two DoFs, hand open/close and forearm pro/supination, were prompted as shown in Figure 2.1. Briefly, the anthropomorphic approach (A) involved following a moving virtual limb, displayed from the user’s perspective [62]. The bar plot (B) displayed the desired activation level and direction of a given direction DoF (similar to the prompting of classification-based approaches, but with a target intensity [61]).

Finally, the Cartesian approach (C) denoted the desired contraction and intensity via mappings to spatial locations, as often done in Fitts' Law testing [19].

Five subjects participated in this portion of the study, completing 5 repetitions of each DoF for each prompting style. Each repetition comprised the sequence: no motion, to DoF -ve direction (e.g., pronation), to DoF +ve direction (e.g., supination), to no motion, to DoF +ve direction, to DoF -ve direction, to no motion. Every movement segment involved a ramp up (2 seconds), steady state (2 seconds), and a ramp down (2 seconds) and periods of no motion lasted 3 seconds. The order of visualizations was randomized for each participant. In all cases, users were asked to map the intensity of their contractions to the corresponding position of the prompt.

2.3.3 User Behaviours

After analyzing the data from the prompting styles described above, a second pilot study was performed. Six subjects completed a training session emulating specific behaviours that had been observed consistently across subjects (anecdotally), followed by an online usability study. The goal of this portion was therefore not to evaluate the specific prompting styles, but to assess the impact of observed behaviours on the usability of the trained regression models. Subjects were coached to elicit two distinct behaviours; *all or nothing* and *anticipation* (explained below in *Results - Prompting styles*), and a baseline case, where they were asked to follow the prompt to the best of their ability. The order of these three cases was randomized for each participant, and 5 repetitions of each DoF were collected in each case. A Cartesian-style prompt was used in this phase due to its prevalence in the literature and similarity to the downstream task [19]. After each round of training, participants performed a 10-trial Fitts' Law-style target acquisition test, as provided by LibEMG [5], to assess the usability of the resulting regression model. To probe the

impact of model linearity, three subjects used a support vector regressor (SVR) with a linear kernel, whereas the other three used a SVR with a non-linear radial basis function (RBF) kernel. A *deadzone* threshold of 0.25 was used for both models to reduce inadvertent activation. Predictions with magnitude less than 0.25 did not elicit movement of the cursor, while movements above 0.25 were not rescaled (i.e., they remained unchanged) [15]. Online usability was assessed using effective throughput, path efficiency, and the number of target overshoots [30]).

2.4 Results

2.4.1 Prompting Styles

Figure 2.2 shows a representation of how users reacted to the different prompting styles, using trends in the observed mean absolute value (MAV) of their EMG signals. The median MAV across channels was used to approximate the strength of the contraction for a given window and the median value across subjects was used to observe the consistency of user behaviours.

These behaviours were consistent enough across subjects that two distinct, anomalous behaviours emerged. The first behaviour, here called anticipation, is exemplified by a preemptive increase in MAV prior to reaching the 0 point of the Cartesian visualization in Figure 2.2, and as later simulated in Figure 2.3. The anticipation behaviour occurs when the user transitions from one end of the DoF to the other too early, meaning that they begin ramping up the other end of the DoF (e.g., hand close) while the prompt (and thus labels) indicate they should be still be ramping down from the previous end of the DoF (e.g., hand open). This occurred more often when the participants travelled from one extreme of the DoF to the other than when beginning from the rest position. This mismatch between behaviour and prompt,

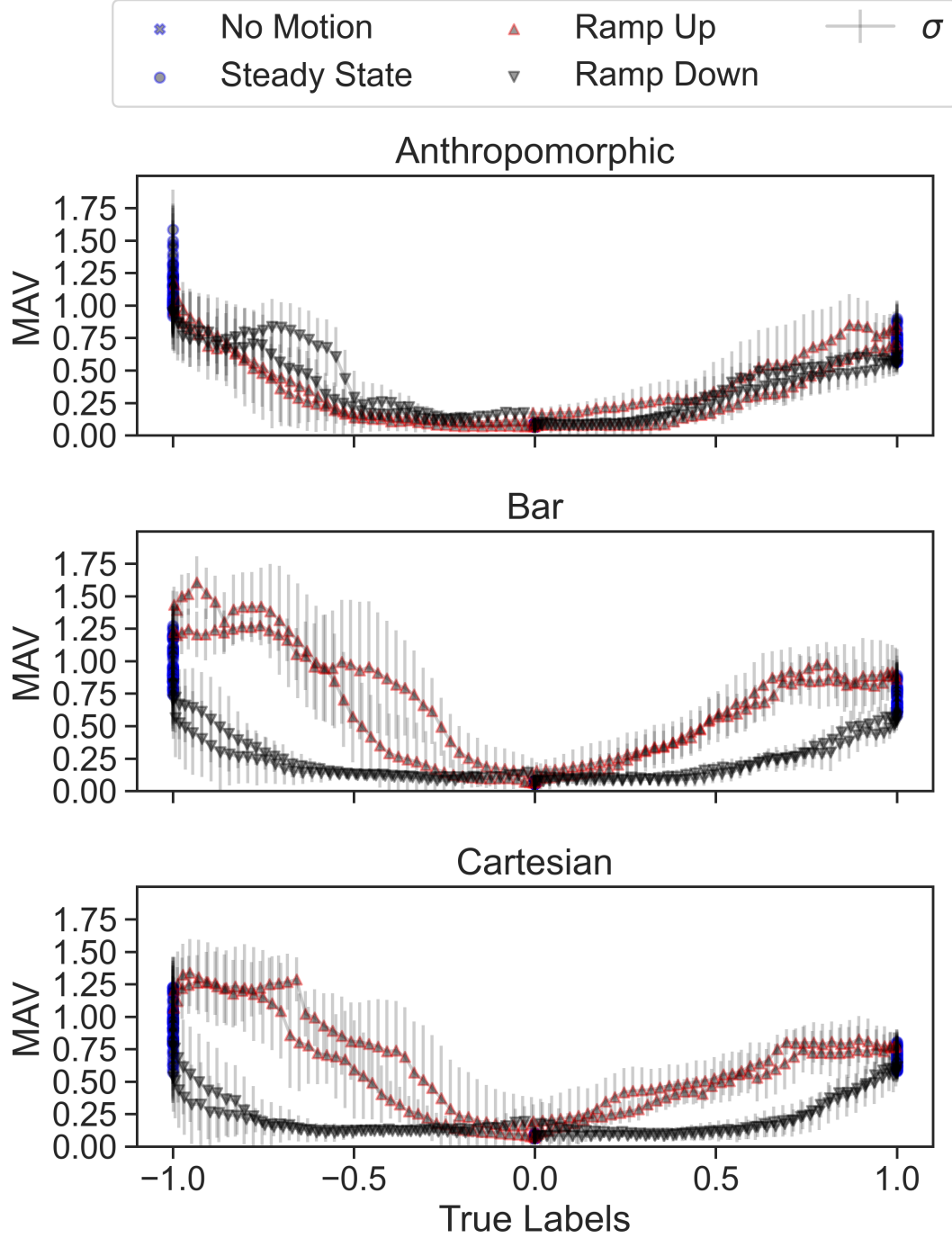


Figure 2.2: Scatter plot of the strength of elicited contraction across subjects as prompting varied for each visualization style during collection of the hand open / close DoF. Each point represents the median MAV across channels and subjects for a single window. The segment of the movement (e.g., ramp up) is determined based on the ground truth labels at that window.

particularly around the rest position, may cause model confusion at low amplitudes and thus problems with quiescence.

The second behaviour, here called *all or nothing*, is exemplified in Figure 2.2 in the Anthromorphic and Bar visualizations, and later simulated in Figure 2.3. From the Anthromorphic case, we see a wide band around 0 where there is no real activation. In the Bar plot case, we see cases where the users goes from rest very quickly to high levels of activation. These combined behaviours represent a lack of gradual modulation from low to high, or high to low. The all or nothing behaviour, in contrast to linearly increasing or decreasing prompts, may lead to poor model fitting and problems with proportional control.

2.4.2 User Behaviours

Based on the previous observations, we explored how these two distinct behaviours may affect the training and usability of the resulting models. To emphasize their effect in this small pilot set, subjects were coached to elicit the identified behaviours, as shown in Figure 2.3. The emulated behaviours exhibited by participants were purposely exaggerated to observe the potential effects of these behaviours on online performance in extreme cases. The MAV trends shown in Figure 2.3 highlight these behaviours, described previously as observed more subtly in *Prompting styles*, including a wider deadzone during the all or nothing emulated behaviour and early ramping up during the anticipation emulated behaviour.

The results of the Fitts' Law testing for each of the behaviours are shown in Figure 2.4. The anticipation behaviour was found to destroy the performance of the linear SVR model, as indicated by the fact that 24 of the 30 total trials could not be completed before the 30 second timeout. Because, the other performance metrics reported in Figure 2.4 cannot be computed unless a trial is completed, this model

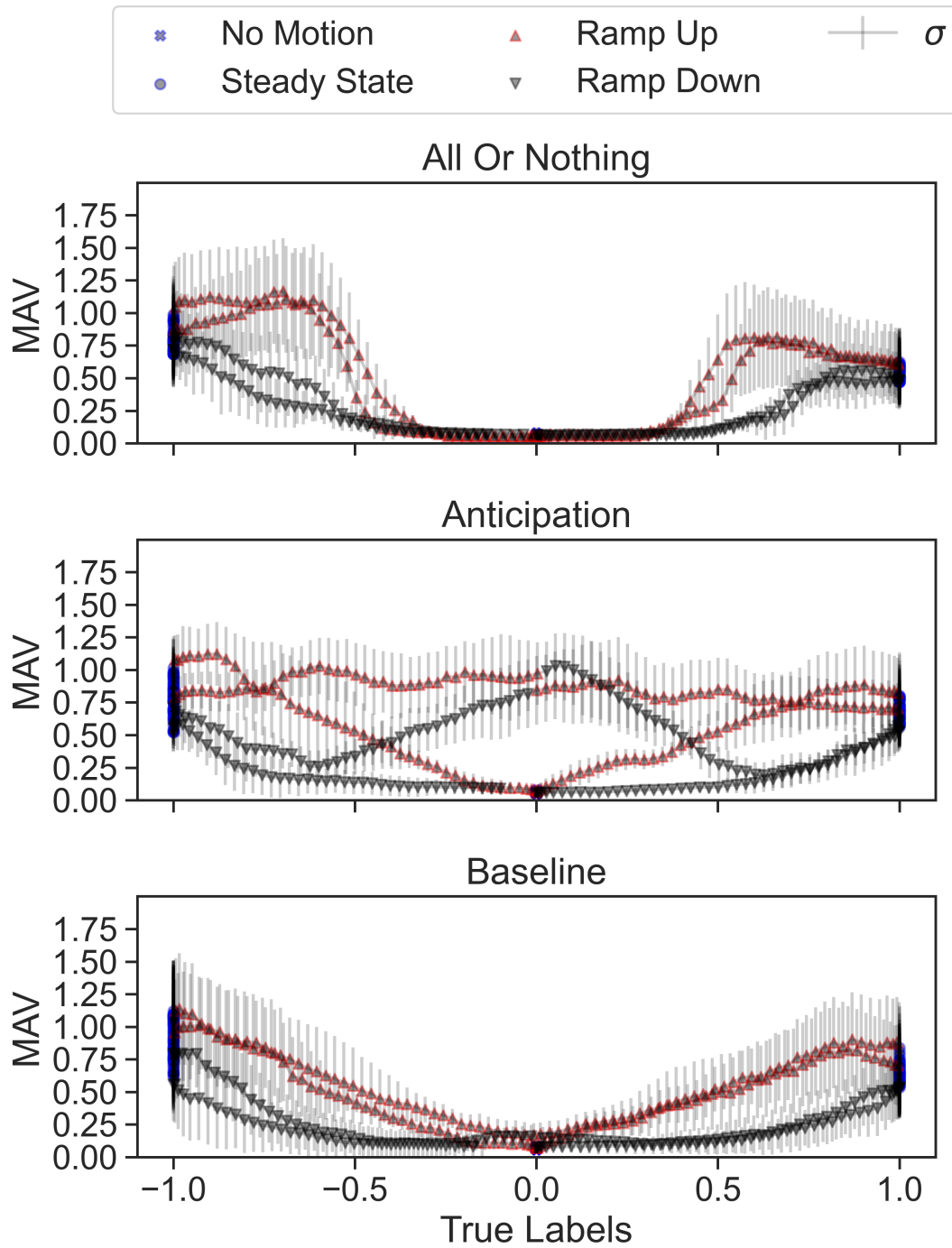


Figure 2.3: Scatter plot of the simulated (and emphasized) behaviours illustrating the strength of contraction across subjects as prompting varied for each observed behaviour during data collection along the hand open / close DoF.

cannot be fairly compared to those of the other behaviours / models. The linear SVR model also degraded when facing the all or nothing behaviour, though not nearly as badly. Contrarily, the non-linear RBF SVR appeared to be quite resilient to the anticipation and all or nothing behaviours.

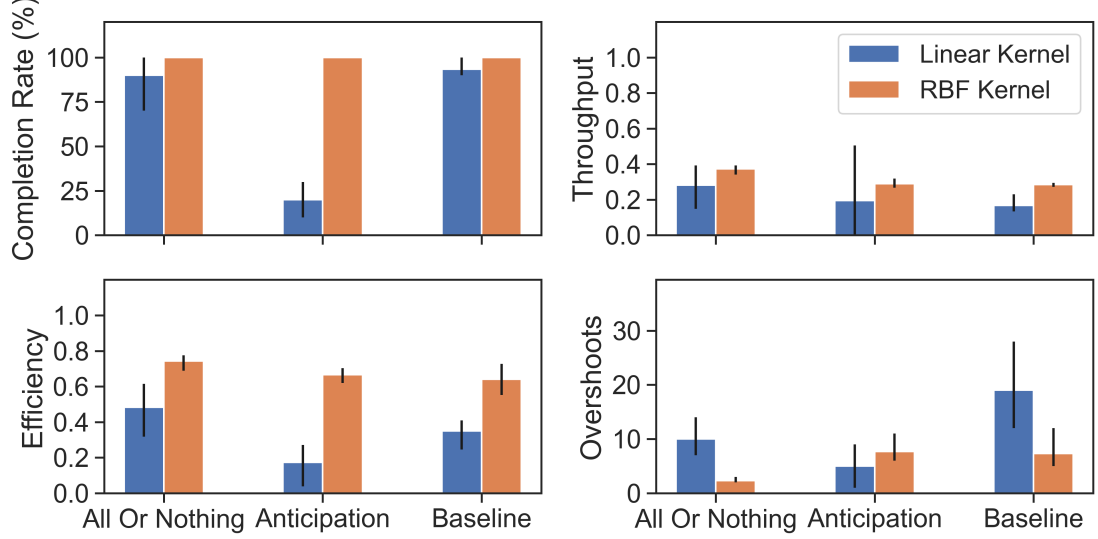


Figure 2.4: Comparison of usability metrics captured via Fitts’ Law test across user behaviours. Each bar represents the mean across subjects, error bars indicate the minimum and maximum values across subjects.

2.5 Discussion

This work describes the early pilot results of a preliminary study aimed to motivate further analysis. Despite modest numbers of subjects, empirical evidence of the impact of prompting style on contraction behaviours was found. Anticipatory behaviours were seen that caused misalignment between the EMG and the given prompts. The observed all or nothing behaviours suggest user difficulties in slowly modulating DoF-specific contraction intensities in alignment with the prompts. The three prompting styles also tended to elicit different behaviours. For example, the clear spatial mapping of the Cartesian case, combined with the green “next destina-

tion” hint, caused more of the anticipatory behaviour. In contrast, associating the desired contraction strength with the position of the hand, as was done with the Anthropomorphic style, may have encouraged more of a position control behaviour leading to the all-or-nothing patterns of EMG. However, in addition to the impact of different prompting styles, many other factors could influence user behaviours, such as the speed at which contractions are prompted, the use of “next motion” hints, and the potential use of real-time feedback to help users better align. Although these results should not be taken as conclusive, they motivate further work on how to best to prompt users when training for regression-based myoelectric control.

The broader goal of this work is to explore the quality of training data and the impact that varying degrees of compliance has on regression performance. To wit, the behaviours that emerged from the prompting investigation led to notable differences in control when evaluated in an online Fitts-style test. Based on these preliminary results, some interesting observations emerged. The non-linear RBF SVR yielded better results than the linear model in general, and may thus be a more resilient solution in accounting for imperfection in training. The large number of timeouts of the linear SVR model with anticipation support this, but also highlight the interplay between model and behaviour. Paradoxically, it appears that the all or nothing behaviour actually led to better usability than the baseline behaviours. It was anticipated that this behaviour may result in a “skating” behaviour wherein the user is unable to stop. However, it is worth noting that a 25% activation threshold was employed across all models in this work, below which the controller would not move. While this was determined empirically to be necessary for usability (as in previous studies [15]), this may have masked the effects of the all or nothing behaviours.

Finally, it is important to acknowledge that this work represents only an initial examination of these effects. The user behaviours were emulated and exaggerated to better evaluated their effects for the small sample size. It also appears that user

behaviours may have model-dependent impacts on usability. Consequently, this work serves mostly to highlight the potential implications of training compliance on model development, robustness, and usability, and warrants further examination.

Chapter 3

Context-Informed Incremental Learning Improves Throughput and Reduces Drift in Regression-Based Myoelectric Control

3.1 Abstract

Despite decades of research, commercially available powered myoelectric prostheses continue to use sequential, classification-based control. While regression-based approaches can improve the dexterity offered through simultaneous, independent, and proportional control, current training protocols lack consistency across studies and fail to capture realistic user behaviours, resulting in robustness issues. To address these challenges, this work employs context-informed incremental learning (CIIL) in

an unconstrained, velocity-based environment for regression-based myoelectric control. Two new adaptive models, one inspired by previous works (O-CIIL) and one modified to factor in user compliance and behaviours (T-CIIL), were compared with two models trained using traditional screen-guided training. Sixteen participants completed an online Fitts’ Law target acquisition task. Both adaptive approaches significantly outperformed ($p < 0.05$) the non-adaptive models across a variety of metrics. Additionally, T-CIIL outperformed O-CIIL in alleviating drift and action interference, key issues that have plagued existing regression-based myoelectric control systems. These findings are supported by two novel metrics, namely *action interference* and *simultaneity gain*, which show that adding simultaneity often increases instability in the form of undesired and uncontrollable simultaneous motions. These findings demonstrate the viability of CIIL in an unconstrained, velocity-controlled environment for regression-based myoelectric control, and highlight the importance of capturing user behaviours when training regression-based myoelectric control systems. Source code is available on GitHub.

3.2 Introduction

Myoelectric control uses electromyogram (EMG) signals to operate an input device, allowing a wide array of interactions in powered prosthetics and human-machine interaction [2, 10]. Despite decades of research and success that have propelled control schemes from traditional dual-site control to state-of-the-art classification-based pattern recognition, the functional capabilities of current prostheses remain somewhat limited [3]. One contributing factor is the need for sophisticated coordination between the hand and wrist for advanced tasks, yet even the most advanced prostheses typically rely on sequential control schemes [3, 14]. For improved dexterity and function, simultaneous control of multiple degrees of freedom (DoFs) has been

desired by prosthesis users since at least 1996 [63]. Although this feature has yet to reach the commercial market, research has shown that it can improve performance and naturalness when completing functional tasks in laboratory settings [44–47].

A variety of methods exist for achieving simultaneous control [45, 64–66], but regression-based control uniquely allows simultaneous and independent proportional control of multiple DoFs [23]. Despite these advantages, much of the myoelectric control field—and commercially available devices—still rely on sequential, classification-based control [67, 68]. Arguably, this is due to concerns about robustness, partially caused by the difficulty associated with training regression-based myoelectric control systems [15, 58]. In contrast to classification-based control schemes that rely on categorical motion classes (e.g., hand open or wrist pronation), regression-based control requires collecting labelled data along each continuous DoF with high granularity. Various supervised training protocols have been used to synchronize these labelled data with EMG signals, including force transducers [20, 22], limb kinematics tracking [9, 19], mirror training (i.e., contra-lateral) [27, 49], and visual prompts [15, 24, 34, 58, 69]. While force and position mappings are viable for able-bodied participants [20], they are not feasible for users with upper limb differences, motivating the use of visual prompts (e.g., a rising and falling bar plot that indicates the strength of the contraction) [15, 16, 24, 37]. However, unlike classification-based tasks, visual prompting in regression not only assumes that the users perform the intended contraction, but also that they closely track changes in the DoF over the entire progression.

Given the likelihood of deviations in compliance and timing, the assumption that the user accurately tracks the contraction strength throughout the data collection process may not always be valid, potentially causing discrepancies between the elicited contractions and the ground truth labels used to train the model [37, 58]. This is concerning, as preliminary findings indicate that such compliance issues degrade on-

line performance [27, 58]. Likewise, changes in the data acquisition protocol—such as the visual prompting style or the amount of steady-state and transience used during a repetition—can drastically impact online performance, further complicating best practices for initial calibration [55, 56, 58]. Whether or not simultaneous motions should be included in the training set also affects performance. For example, some studies suggest that simultaneous motions are unnecessary in the initial calibration [18, 19, 23], while others recommend their inclusion [25, 26], and some offline results even demonstrate simultaneous motions in the initial calibration actually harm performance of isolated movements [34]. Altogether, the many uncertainties surrounding regression-based myoelectric control system calibration and the compliance issues that ultimately arise likely contribute to its limited adoption. This leads to several unsolved issues including poor performance during periods of *quiescence* (i.e., unintended cursor or prosthesis drift when the user wants to stop) [15, 34, 58] and high *action interference* (i.e., unintended activation of other DoFs when the user tries to perform a single DoF action) [15–17, 34, 35].

To overcome these challenges, this work leverages a recently proposed approach, *context-informed incremental learning* (CIIL) [29], to acquire realistic user-in-the-loop data as users interact with the system. We compare four different training protocols, two traditional non-adaptive approaches and two CIIL-based adaptive approaches, to demonstrate three primary contributions. First, we demonstrate, for the first time, the viability of CIIL in an unconstrained, velocity-based regression environment and show that adaptive models significantly improve performance in all facets of myoelectric control measured in this work. Next, we show that previous implementations of incremental learning in regression-based myoelectric control make naive assumptions about user behaviours, and that modifying the adaptation process to improve robustness to these behaviours mitigates robustness issues in downstream models. Lastly, we employ multiple metrics, including two newly proposed - namely

action interference and *simultaneity gain* - to demonstrate that naively adding simultaneity often results in instability in the form of undesired and uncontrollable simultaneous motions. Overall, this work provides insights into how the training protocol affects performance, simultaneity, and user experience, highlighting the importance of considering user behaviour when training myoelectric control systems.

3.3 Background

3.3.1 Adaptive Learning

To avoid the noted challenges of screen-guided training (SGT) for regression and to capture more realistic control behaviours, researchers have begun collecting training data for regression-based systems in real-time co-adaptive environments (where the user and algorithm are adapting at the same time) [23,31–33,38,70–72]. For example, many have employed the approach proposed by Hahne et al. [23], where a linear regressor is adapted in real-time by using the target *position* as the ground truth label [38,71]. Despite its efficacy, the approach used by Hahne et al. [23] can be sensitive to hyperparameter selection, prompting others to explore the use of unsupervised adaptation in position control [33,72]. Building on these adaptation strategies, Chou et al. [31] have shown that co-adaptive learning is viable in a *velocity*-controlled environment both when using a goal target and when using eye gaze coordinates as ground truth labels, demonstrating potential uses in real-world systems. While these co-adaptive approaches have been shown to outperform SGT in regression-based myoelectric control for persons with and without limb difference [23,38], previous implementations have been limited by two main drawbacks: 1) the use of position control and 2) naive assumptions about user compliance.

First, previous uses of co-adaptation for regression-based myoelectric control often

use position-based control due to the challenges of acquiring the proportional control magnitude and assessing simultaneity in a velocity-based environment [23, 32]. Modern powered prostheses, however, use velocity control. This remarkably different paradigm (wherein EMG patterns are mapped to the device’s velocity and not its position) limits the potential to capture real use-case behaviours during position-based training. Of the approaches that have been evaluated in a velocity-controlled environment [31, 71], users were shown a pre-defined path and told to mimic the velocity of the cursor based on real-time feedback. While these approaches are a step in the right direction, they do not give the user agency in how they accomplish a task. For example, in [31], it was assumed that the velocity of the cursor should be proportional to the cursor’s distance from the target. While this is a fair assumption, previous work suggests that users act primarily at two speeds: (1) fast and imprecise and (2) slow and precise [29]. Correspondingly, the constraints placed on learning in these environments limit the goal-oriented behaviours that they can capture.

The second limitation is that previous works assume that the user is either on (for position-based), or going directly to (for velocity-based), the target [23, 31]. Due to the complexities of regression-based control, users often do not travel in the optimal direction, invalidating this oversimplified assumption. For example, Smith et al. found that users often use 1-DoF movements for finer movements near the target [69]. In this case, assuming that the user is always travelling along the optimal path would relabel 1-DoF movements as multi-DoF movements, providing the model with incorrect pseudo-labels and likely contributing to action interference (the unwanted activation of additional DoFs). We, therefore, argue that previous attempts at co-adaptation in regression environments have been built upon naive assumptions about the user and may not address some of the key issues hindering regression-based myoelectric control.

3.3.2 Context Informed Incremental Learning

Shifting the paradigm away from conventional methods of the historically used screen-guided or prosthesis-guided training, CIIL is a training approach that has previously shown promise for classification tasks [29, 39, 40]. By relying solely on the context provided by the environment (i.e., whether the user is accomplishing the general goal of the training environment, such as moving towards a target along any axis), CIIL enables flexible and sample-efficient user-in-the-loop adaptation. For example, it has been shown that CIIL can adapt a model with a limited amount of training data (1 second per class) [40], in the case of a catastrophic electrode shift [39], and can even learn from scratch and outperform traditional SGT approaches [29]. Moreover, this approach is suitable for simple statistical models like Linear Discriminant Analysis and more complex deep learning architectures.

CIIL leverages every model prediction and the contextual suitability vector for that action. For example, in the case of a target acquisition task, the action might move the cursor to the right, and the possible contextual suitability vector is ['Up' 'Right', 'Nothing'] since the target is up and to the right. Alternatively, the suitability vector might be ['Wrist Pronation', 'Hand Close', 'Nothing'] when approaching an object like a tennis ball with a prosthesis. If the action taken by the controller aligns with the suitability context vector, this is considered to be a positive context match, and the model's decision should be reinforced. In contrast, if they do not align, the context match is negative, and the model's parameters should be updated to reflect this error. If there are multiple suitable choices, soft labels can be used to update the model to eliminate issues associated with guessing [29]. Correspondingly, the only assumption of this approach is that user behaviours generally align with the goals of the tasks (e.g., they are trying to acquire the targets). Although similar to reinforcement learning [32], CIIL is much more sample efficient because the context extracted from

the environment limits its need for exploration. Moreover, compared to previous adaptive approaches, there is no direct assumption of velocity or direction. While this approach has never been employed in a regression environment, it is hypothesized that it will be suitable for overcoming many of the limitations of current training approaches.

3.4 Methods

3.4.1 Participants

Sixteen participants (ages 22-32, 8 male, 8 female) took part in this experiment as approved by the University of New Brunswick Research Ethics Board (REB 2022-122). Informed consent was obtained from all participants in accordance with the Declaration of Helsinki, and no incentives were provided. The experiment lasted approximately one hour.

3.4.2 Signal Processing

LibEMG, an open-source Python library for processing EMG, was used to facilitate data streaming, the creation of visual prompts, the presentation of the online validation environment, and real-time myoelectric control [5]. A 2nd order highpass filter ($f_c = 20$ Hz) was applied to reduce DC noise and motion artifact, and a 3rd order notch filter ($f_c = 60$ Hz) was used to reduce power line interference. The Thalmic Labs Myo Armband, a wearable 8-channel cuff with a sampling frequency of 200 Hz, was placed on the participant’s dominant forearm. EMG signals were segmented into 150 ms windows with an increment of 40 ms. Wavelet energy (WENG) features were then extracted from each window and passed to the model for real-time

prediction [73].

3.4.3 Data Acquisition

All SGT-based data used to initialize or fully train the various models were collected using *mimic* training, a standard protocol used throughout the field for collecting training data for regression-based myoelectric control systems [16, 24, 27, 34, 58]. Briefly, participants were asked to follow (*mimic*) a moving cursor in real-time and the values at each frame were used as ground truth labels. Similar to other works [18, 19, 58], a point moved along a Cartesian plane, where the x-axis represented one DoF (hand open/close) and the y-axis represented the other DoF (wrist rotation). Participants were asked to map the strength of their contraction to the position of the point in real time as it moved in multiple directions. For isolated (single DoF) motions, a 50-second repetition of SGT was composed of ten 2-second oscillations along the x-axis for the first DoF (hand open/hand closed), followed by 5 seconds of rest, followed by ten 2-second oscillations along the y-axis for the second DoF (wrist pronation/wrist supination), followed by another 5 seconds of rest. For simultaneous motions (both DoFs active), participants followed a similar pattern but the cursor’s path was rotated 45° to prompt both DoFs simultaneously.

3.4.4 Models

Four distinct models were investigated to compare the effects of including combined motions in the calibration data, adapting with user-in-the-loop data, and mitigating assumptions about user compliance. All models used the same underlying neural network architecture but were trained using different protocols. The selected architecture was informed by previous work [29], initial piloting, and the need to avoid potential effects introduced by temporal models, which have not yet been explored

in the context of CIIL. Each model was composed of a multi-layer perceptron with layers of 64, 32, 10, and 2 neurons. Batch normalization, a rectified linear unit activation function, and dropout ($p = 0.2$) followed each linear layer except the last. Training for all models used the Adam optimizer, L1 loss, and a batch size of 64 windows. All models were provided with 300 seconds of training data, acquired from SGT and/or CIIL adaptation, followed by 300 seconds of online validation in a Fitts' Law environment. For non-adaptive models, the training data consisted of 300 seconds of SGT-acquired data. For the adaptive models, training data comprised 50 seconds (i.e., 1 repetition) of isolated SGT data followed by 250 seconds of CIIL-based adaptation. In this way, participants spent the same amount of time collecting data for both the adaptive and non-adaptive approaches, and each was given the same amount of data for model training. For each model, participants underwent a training phase, followed by a 5-minute validation phase, and then completed a survey before proceeding to the next model. The order of the models was balanced across participants using a Latin square design. Each model is described in detail below.

3.4.4.1 W-SGT

A conventional non-adaptive model trained for 150 epochs using 300 seconds of SGT data collected from isolated, within-DoF motions (thus *W-SGT*).

3.4.4.2 C-SGT

A conventional non-adaptive model trained for 150 epochs using SGT data, with 150 seconds collected from isolated motions and 150 seconds from simultaneous, combined-DoF motions (thus *C-SGT*).

3.4.4.3 O-CIIL

An adaptive model seeded with 50 seconds of SGT data followed by 250 seconds of user-in-the-loop co-adaptation. The model used as a starting point for adaptation was trained for 150 epochs using only isolated motion SGT data. For each prediction made by the model throughout the adaptation phase, pseudo-labels were created based on the context of the environment and added to a memory buffer. Once new data were added to the buffer, the model was trained for 5 epochs with all the data currently available (i.e., SGT data + pseudo-labels collected during adaptation). Data were continuously being added to the memory buffer at all times, so any data that were collected while the model was adapting were used once the model was ready for the next round of adaptation. Pseudo-labels were created following an *oracle*-based approach (thus *O-CIIL*), so the user was assumed to be going directly to the target at all times during the adaptation phase. The magnitude of the pseudo-label vector was determined based on the distance between the cursor and the target at the time of the prediction, a novel concept introduced in this work. The relationship between target distance and proportional control magnitude (see Equation 3.1) was determined based on piloting.

$$p = \min(1, \sqrt{\frac{d - TR}{IR}}) \quad (3.1)$$

where d is the distance between the cursor and the target, TR is the target radius, IR is the ISO Fitts' radius (i.e., the radius of the circle that defines the target locations), and p is the corresponding proportional control magnitude of the pseudo-label vector. Equation 3.1 was formulated to normalize based on the distance between the targets with a maximum value of 1.

3.4.4.4 T-CIIL

An adaptive model seeded with 50 seconds of SGT data followed by 250 seconds of user-in-the-loop co-adaptation. The model used as a starting point for adaptation was trained for 150 epochs that only used isolated motion SGT data. For each adaptation, the model was trained for 5 epochs. As with O-CIIL, T-CIIL used the mapping from target distance to proportional control shown in Equation 3.1. Instead of assuming that the user always took the optimal path to the target, however, T-CIIL employed a tolerant approach (thus *T-CIIL*) by using the context of the task to modify the pseudo-labels to mitigate known issues associated with user compliance (i.e., the model is aware that user behaviours may deviate from the optimal action and can *tolerate* these variations). As shown in Figure 3.1A, pseudo-label creation was first informed by the direction of the prediction. For each prediction, the cursor was assumed to be at the origin of an axis and the prediction vector. The subsequent pseudo-label was then crafted based on the quadrant of the prediction. If the prediction fell in the quadrant opposite of the target (quadrant 3, in this case), no pseudo-label was generated, and the prediction was excluded from adaptation (though the cursor still moved in that direction). If one of the components was correct (quadrants 2 or 4 in this case), the resultant pseudo-label pointed in the direction of only the correct component (i.e., on-axis). If both components were in the correct direction (quadrant 1 in this case), the pseudo-label vector pointed in the optimal direction to the target (similar to O-CIIL). This decision flow was used to create pseudo-labels in most cases, but there were two cases where it did not apply. First, as shown in Figure 3.1B, if the cursor was in line with a target in either component, the pseudo-label pointed solely to the correct component that would move the cursor to the target. Second, as shown in Figure 3.1C, an activation threshold was employed to improve robustness to periods of no activation (e.g., after a target was acquired or if a user was slow to respond) being labelled as high-magnitude

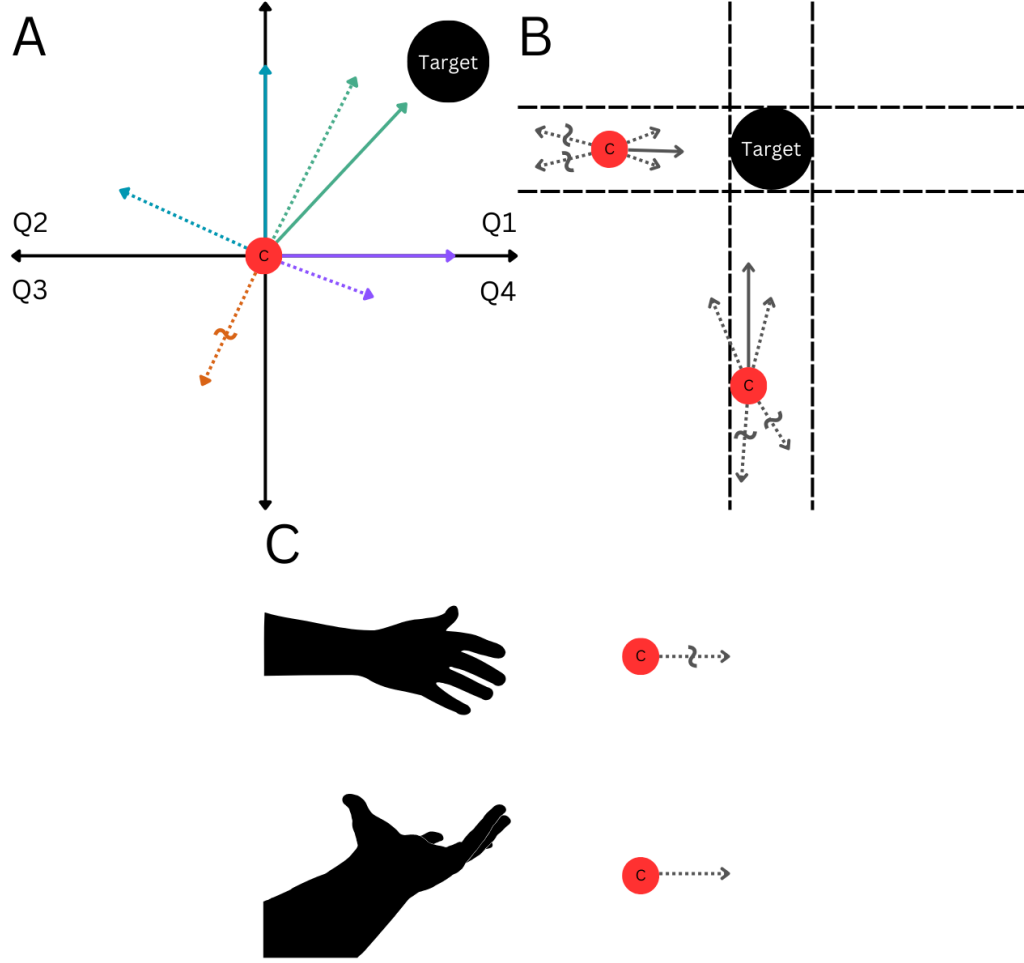


Figure 3.1: Illustration of pseudo-label creation for T-CIIL. Predictions are represented by dotted arrows and corresponding pseudo-labels are represented by solid arrows in the same colour. The red dot, labelled “C,” represents the current cursor position, and the black circle, labelled “Target,” shows the current goal target. Arrows marked with the “~” symbol represent predictions that were considered poor for adaptation and have been ignored. A) Example of main pseudo-label decision flow. Predictions in the correct quadrant (green) are relabelled to point in the optimal direction to the target. Predictions for which one component is correct (blue and purple) are relabelled to point in the direction of the correct component. Predictions where neither component is in the correct direction (orange) are ignored. The magnitude of the corresponding pseudo-label vector is determined based on the distance from the cursor to the target. B) Illustration of target runways. In the case where the cursor is in line with the target (i.e., they can reach the target by moving in a single component), only the component that requires movement to reach the target is reinforced. C) Visualization of activation threshold. For all decisions, pseudo-labels are only created for adaptation if the model input is above the activation threshold (determined based on no motion data from calibration).

predictions. Data were then only used for adaptation if the level of EMG activity (i.e., the mean wavelet energy across the frequency bands) was above this activation threshold. To avoid spurious labelling of low-intensity contractions, this decision was computed as a majority vote of the 5 most recent windows. The activation threshold (see Equation 3.2) and the number of decisions in the majority vote were determined empirically through pilot experiments.

$$at = \mu_{WENG}^{NM} + 0.2\sigma_{WENG}^{NM} \quad (3.2)$$

where μ_{WENG}^{NM} is the mean of the wavelet energy of all no-motion samples (i.e., both components have a label of 0) in the calibration data, σ_{WENG}^{NM} is the standard deviation of the no motion samples in the calibration data, and at is the activation threshold.

3.4.5 Online Validation Task

Each model was evaluated using an ISO 9241-9 inspired Fitts' Law validation task shown in Figure 3.2 [1]. Pilot work found that mapping wrist rotation to vertical movement on a Cartesian plane was unintuitive for many participants, so the target-reaching task in this work was modified to map wrist rotation to the rotation of a cursor in a Polar plane. The direction of rotation was modified based on the handedness of the user to provide the most intuitive mapping (i.e., pronation rotated the cursor counter-clockwise for right-handed participants and vice-versa for left-handed participants). Hand open/close was mapped to the radius of the aperture, where the aperture was a circle with the origin centered at the bottom of the screen. The underlying cursor locations were recorded in a Cartesian plane and then rendered to the screen in the Polar plane to ensure the calculation of downstream usability

metrics was unchanged. To acquire a target, the user had to move the cursor into the current goal target and dwell within the target for 2 consecutive seconds. Once the cursor was in the target, the cursor colour changed to blue and a 2-second timer was shown in the top left of the screen. If the user did not acquire the target within 10 seconds, the trial was considered a failure and the next trial began with a new target. Participants were informed that they could move simultaneously and were encouraged to do so, but simultaneous motions were not required to acquire the target.

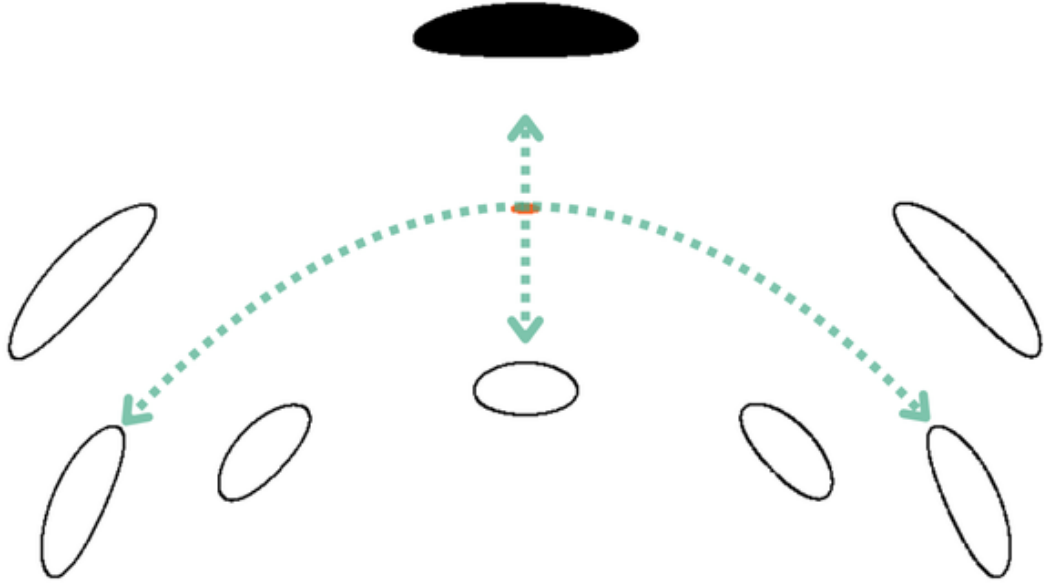


Figure 3.2: Online ISO 9241-9 inspired Fitts' Law task [1]. Targets are drawn in black and the cursor is drawn in orange. The current goal target is filled in, while potential target locations are outlined. Green arrows annotate the two DoFs, but this was not shown to the user during the experiment. As shown by the vertical arrow, hand open/close increases and decreases aperture size, respectively. effectively moving the cursor in the vertical direction. As shown by the curved arrow, rotating the wrist rotates the cursor in the corresponding rotational direction, where the direction of the mapping was dependent on the handedness of the participant.

Eight online usability metrics were used to evaluate models in this work to analyze multiple components of myoelectric control. A trial was considered successful if it was acquired and dwelled in for 2 seconds within a 10-second timeout. To account for the user learning, the first 20 trials (during which the average performance across users

began to plateau) were considered warm-up trials and excluded from the calculation of validation metrics. Validation metrics were computed using the remaining trials. Trials that timed out were still included in the calculation of performance metrics, and were optimistically assigned a movement time of 10 seconds (i.e., equal to the timeout). Each usability metric is described below.

3.4.5.1 Throughput

Throughput describes the amount of control information that can flow through the system [1]. It is a measure of the difficulty of the task (see Equation 3.3) and the speed at which it was completed (see Equation 3.4).

$$ID = \log_2\left(\frac{D}{W} + 1\right) \quad (3.3)$$

where ID is the index of difficulty, D is the distance from the cursor starting position to the center of the target, and W is the width of the target.

$$Throughput = \frac{ID}{MT} \quad (3.4)$$

where MT is the time taken to acquire the target. The dwell time is subtracted from the movement time for successful trials.

3.4.5.2 Path Efficiency

Path efficiency compares the path taken to acquire the target to the most optimal path, offering insight into the control of simultaneous motions [30]. It is a measure of the distance travelled relative to the minimum distance required to reach the target (see Equation 3.5).

$$Path\ Efficiency = \frac{FP}{DT} \times 100\% \quad (3.5)$$

where FP is the optimal (i.e., fastest) path to the target from the cursor's starting position and DT is the total distance travelled during the trial.

3.4.5.3 Overshoots

Overshoots are a count of the number of times the cursor enters the target and then exits before it is finally acquired [30]. Overshoots help quantify the ability to stop and stay at rest when desired.

3.4.5.4 Completion Rate

The completion rate measures how many targets were successfully acquired before the timeout relative to the total number of trials (see Equation 3.6).

$$Completion\ Rate = \frac{ST}{T} \times 100\% \quad (3.6)$$

where ST is the number of successful trials and T is the total number of trials.

3.4.5.5 Number of Trials

The number of trials (successful or unsuccessful) reached was able to be computed as a metric in this work because the validation trial was based on a time limit for each model instead of a set number of trials.

3.4.5.6 Action Interference

A novel metric was used to quantify the action interference exhibited by the controller (see Equation 3.7). Action interference occurs when the participant attempts to move in isolation (on activating one DoF), but an unintended activation occurs in a different DoF, causing undesired simultaneous motion [17]. It was assumed that the user wanted to move in isolation when they were aligned with the target in one DoF, so action interference was calculated as the total distance travelled in the DoF associated with an axis that the cursor was already aligned in (i.e., if the cursor was below the target, movement to the left or right increased action interference). This metric describes the distance travelled in an unintended DoF, so a lower value indicates better performance. Trials where the cursor did not align with the target at any point were excluded when calculating action interference.

$$\text{Action Interference} = \frac{1}{S_x} \sum_{i=1}^{S_x} |p_x(i)| \quad (3.7)$$

where S_x is the number of samples where the cursor is in line with a target in a single component (i.e., only a single DoF activation is needed) and p_x represents the predictions associated with the unwanted component (e.g., in a Cartesian space, the unwanted component would be movement in the x-axis if the cursor was already directly below the target).

3.4.5.7 Drift

Drift occurs when the user wants to be at rest, but the cursor continues to move. It was assumed that the participant wanted to be at rest when in the target, so drift was quantified as the distance travelled while in the target (see Equation 3.8). Trials where the cursor did not enter the target at any point were excluded when

calculating drift.

$$Drift = \frac{1}{S_a} \sum_{i=1}^{S_a} \|p_a(i)\|_1 \quad (3.8)$$

where S_a is the number of samples where the target is acquired (i.e., the cursor is inside the target), p_a represents the predictions made while the cursor was in the target throughout the entire trial, and $\|\cdot\|_1$ indicates the L1 norm.

3.4.5.8 Simultaneity Gain

The amount of time spent moving simultaneously (see Equation 3.9) can capture how much simultaneity was used, but not whether this simultaneity was useful or intentional. Simultaneity gain, a novel metric proposed in this work, was devised to measure how well the participant could control the additional simultaneity provided by the model (see Equation 3.10). Models that provided higher simultaneity but similar path efficiency would suggest that the additional simultaneity could not be leveraged fully or did not add value, so the resulting simultaneity gain is lower. Trials that did not have any simultaneous predictions were excluded when calculating simultaneity gain.

$$\% \text{ Simultaneity} = \frac{S_s}{S} \quad (3.9)$$

where S_s is the number of samples where both predictions are greater than 0 and S is the total number of samples.

$$\text{Simultaneity Gain} = \frac{\text{Path Efficiency}}{\% \text{ Simultaneity}} \quad (3.10)$$

3.4.6 Statistics

All data were first checked for normality using the Shapiro-Wilk test. For those metrics that exhibited a normal distribution (throughput and trials complete), a repeated-measures ANOVA was conducted to determine if there were significant differences ($p < 0.05$) between models. For metrics that showed significant effects in the ANOVA, pairwise comparisons were performed using Bonferroni correction to identify which specific models differed significantly. For metrics that showed non-normal distributions (path efficiency, overshoots, completion rate, action interference, drift, and simultaneity gain), a Friedman test was conducted to determine if there were significant differences between models. Follow-up pairwise Nemenyi tests were performed to identify which models differed significantly. All stats were computed in R.

3.5 Results

3.5.1 Adaptive Models Outperform SGT Models

The primary goal of this work was to demonstrate the viability of co-adaptive models in an unconstrained, velocity-based regression environment and contrast them against non-adaptive protocols used throughout the field. Despite using equal amounts of training data, the usability metrics shown in Figure 3.3 demonstrate that the adaptive CIIL models outperformed both non-adaptive SGT models on average for most metrics. O-CIIL significantly ($p < 0.05$) outperformed W-SGT in throughput, overshoots, trials, and completion rate, and C-SGT in throughput, path efficiency, and trials. Similarly, T-CIIL significantly ($p < 0.05$) outperformed W-SGT in all metrics except action interference and simultaneity gain, and was

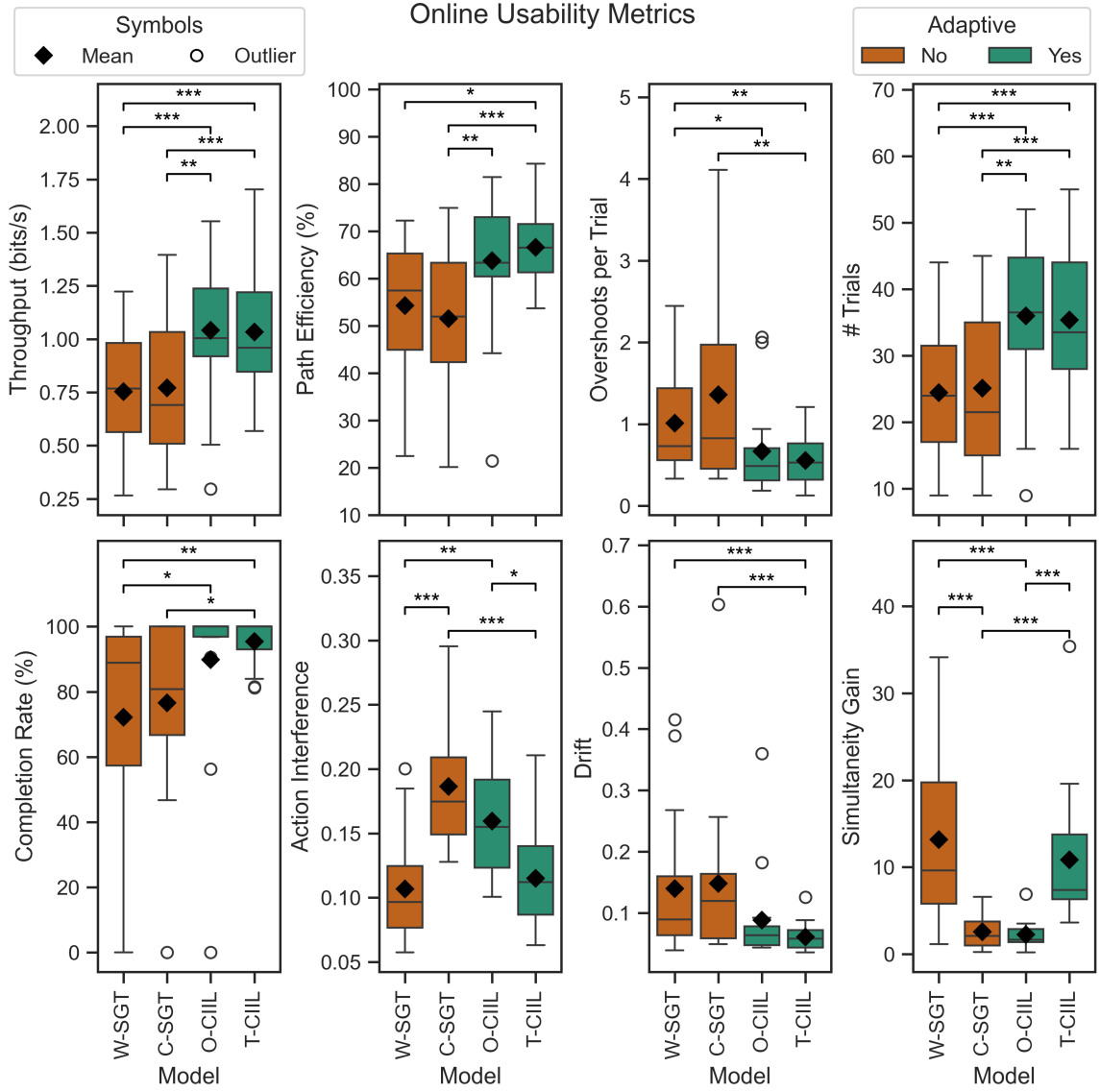


Figure 3.3: Summary of online usability metrics over the validation period. The first 20 trials were excluded as they were deemed ‘user learning’ trials. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

significantly better than C-SGT in all metrics ($p < 0.05$).

In contrast to the other usability metrics, W-SGT performed the best in terms of action interference, significantly improving action interference and simultaneity gain compared to C-SGT and O-CIIL ($p < 0.01$). Similarly, T-CIIL significantly outperformed C-SGT and O-CIIL for action interference and simultaneity gain ($p < 0.05$). Furthermore, T-CIIL was roughly equivalent to W-SGT on average for both metrics.

The loss curves shown in Figure 3.4 confirm that the L1 loss monotonically decreased while training with SGT data and began to plateau, but that the loss increased again when incorporating new behavioural data using the adaptive models. Despite this, Figure 3.5 shows that throughput steadily increased over the adaptation phase. Figure 3.5 also shows that the throughput over the validation period exhibited a small learning effect that was similar across all models.

3.5.2 The Effect of User Compliance Adjustments in an Adaptive Setting

The proposed novel method for capturing goal-oriented behaviours in a co-adaptive setting leveraged context from the environment while acknowledging known issues with user compliance to improve the creation of pseudo-labels for adaptation. The upward trend in throughput over time shown in Figure 3.5 confirms that the user and model co-adapted effectively throughout the adaptation period for both adaptive approaches, but each adaptive approach offered subtle differences. For example, Figure 3.4 shows that the loss throughout the adaptation period increased noticeably more for O-CIIL than T-CIIL. The differences observed during the adaptation phase continued into the validation phase, leading to distinct performance trade-offs. As shown in Figure 3.3 and 3.6, the modifications made to T-CIIL improved path

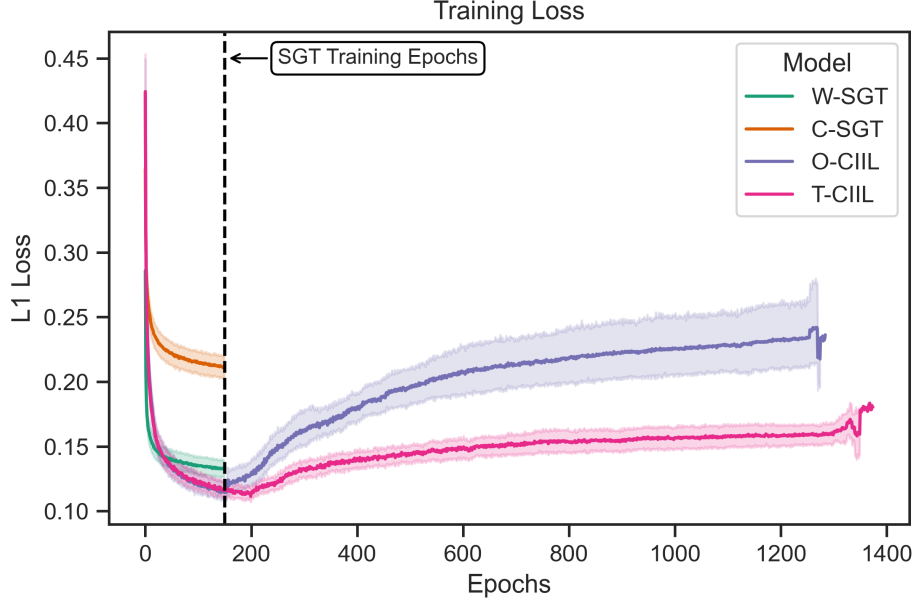


Figure 3.4: The L1 loss for each model. The mean across participants is shown as a solid line, and 95% confidence intervals are shown as shaded regions. Loss after the dotted line represents the loss during the adaptation period. The sudden changes in the mean and confidence intervals at the end of the loss curves for the adaptive models are simply a byproduct of the different number of epochs per participant during the adaptation period.

efficiency, overshoots, completion rate, action interference, drift, and simultaneity gain, but not throughput or number of trials relative to O-CIIL. Among the online metrics, a significant difference between the two adaptive approaches was found only for action interference ($p < 0.05$).

3.5.3 The Cost of Simultaneity

Non-adaptive SGT models with and without combined motions in the calibration data were tested in this work to confirm the impact of adding simultaneous training data. Participants used far more simultaneity with C-SGT based on Figure 3.6, but this simultaneity was not always beneficial. As demonstrated by Figure 3.3, C-SGT had a higher throughput than W-SGT, but the worsened performance in overshoots, action interference, drift, and simultaneity gain suggests that it came at

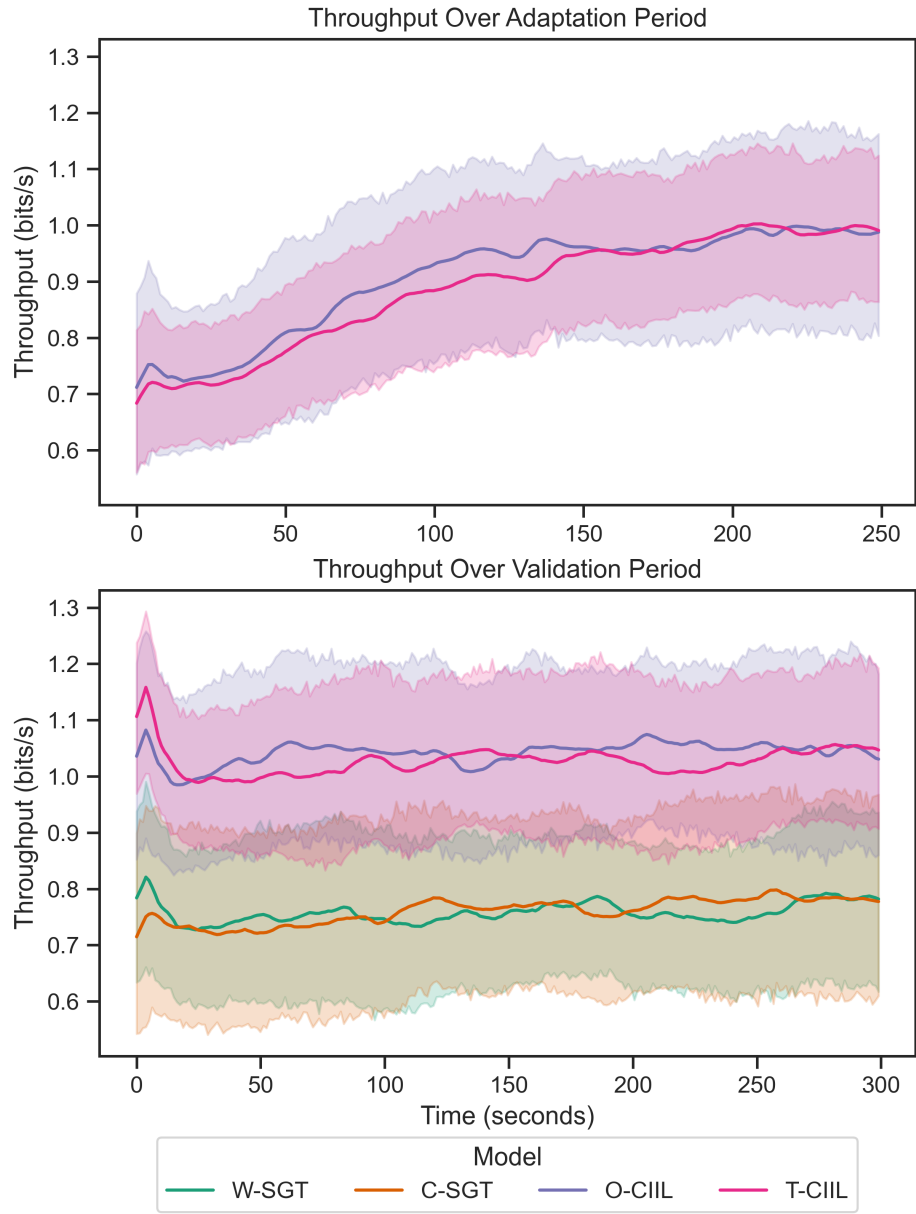


Figure 3.5: A rolling average ($N = 60$ seconds) of throughput over time during the adaptation (left) and validation periods (right). The mean across participants is shown as a solid line, and the 95% confidence intervals are shown as shaded regions.

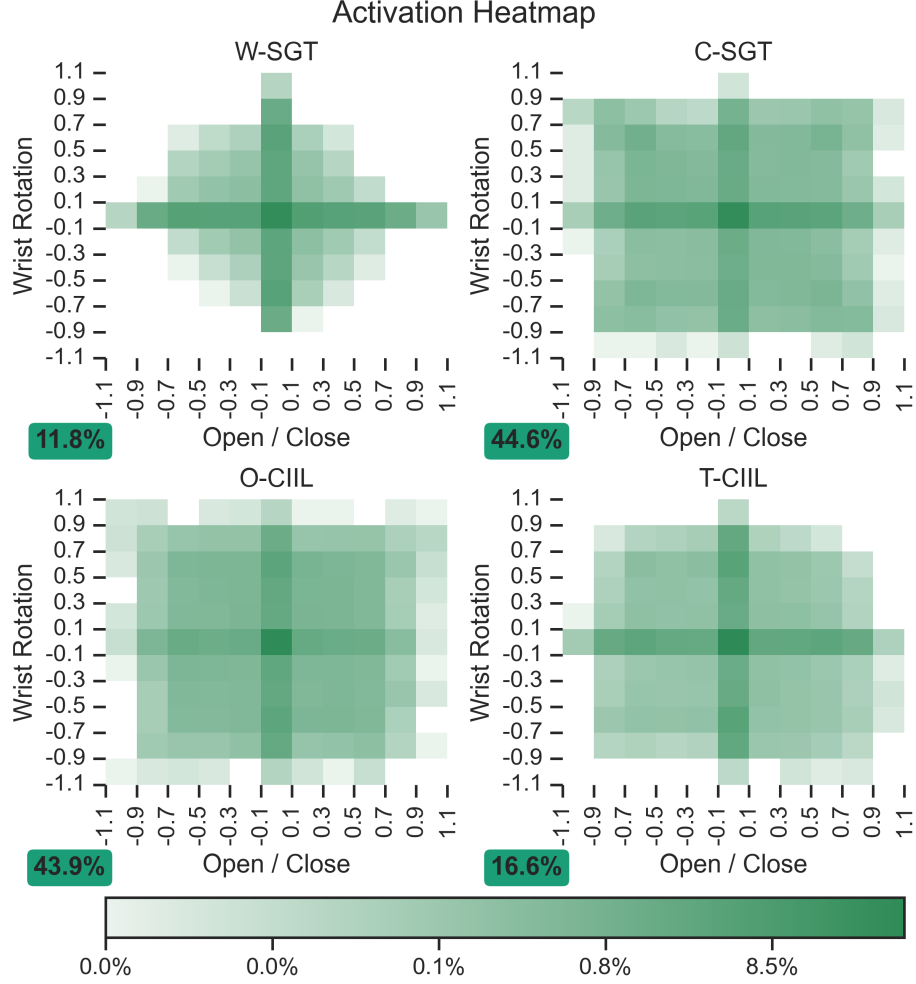


Figure 3.6: Visualization of the use of simultaneity per model based on model predictions during the validation period. The heatmaps show the frequency of each activation level for both DoFs at once. The total % simultaneity (see Equation 3.9) for each model is annotated in a text box below the corresponding heatmap.

a cost of higher instability. As reflected in the significant difference in simultaneity gain ($p < 0.001$), Figure 3.3 shows that C-SGT had worse path efficiency than W-SGT on average despite the marginal increase in simultaneity used. The same can be said for the adaptive models, where T-CIIL had less than half the % simultaneity of O-CIIL but improved path efficiency and significantly better simultaneity gain ($p < 0.001$).

3.5.4 Participants Preferred Adaptive Models

In addition to the objective performance results, subjective results were captured in the form of survey questions. Figure 3.7 showcases the opinions expressed by participants for each model based on multiple aspects of control. Generally, participants preferred adaptive models over non-adaptive models based on survey results, but the difference between adaptive models was not as apparent. T-CIIL was rated higher than or equal to O-CIIL for questions involving control, but T-CIIL was rated lower regarding the control of the cursor’s speed. Additionally, it was found that participants generally found the actual training protocol of the adaptive approaches more engaging.

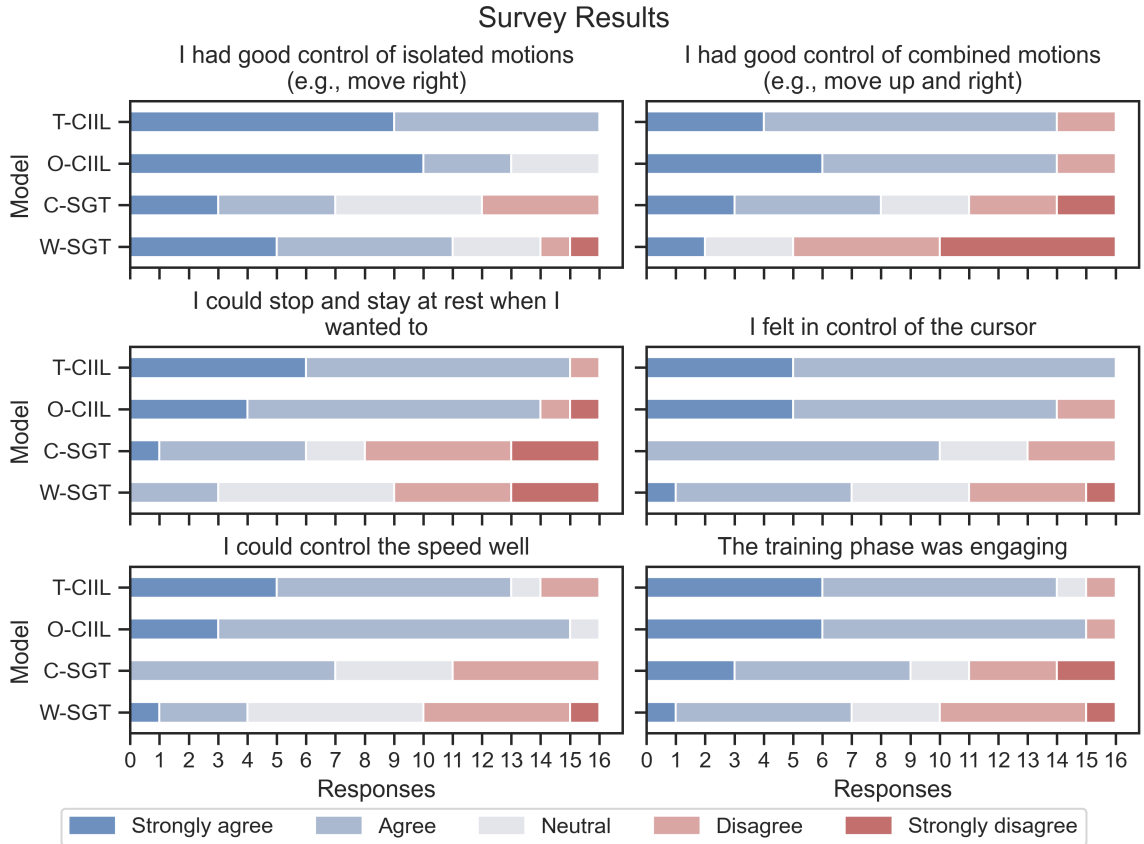


Figure 3.7: Results of the survey posed after each model was used. The distribution of answers for each question are shown.

3.6 Discussion

The results of this work highlight some key challenges associated with regression-based myoelectric control, particularly regarding how the training protocol can drastically affect usability. Previous uses of co-adaptation [23,32,38] have shown promising performance compared to models trained using SGT, but have made assumptions about user behaviours and compliance and often employ position-based control instead of velocity-based control. First and foremost, this work shows that co-adaptation can be achieved in an unconstrained, velocity-based environment and that models trained using this approach are significantly better. Both adaptive CIIL approaches outperformed the SGT approaches in all metrics except for two, showcasing that carefully planned co-adaptive approaches can overcome many of the challenges associated with regression-based myoelectric control. The only metrics where adaptive models did not outperform non-adaptive models were action interference and simultaneity gain, for which W-SGT had the best values, significantly better than C-SGT and O-CIIL. This result may be misleading, though, because W-SGT predicted far fewer simultaneous motions in general than the other models. Despite this, T-CIIL was roughly equivalent to W-SGT on average for both metrics while significantly improving path efficiency, highlighting the benefit of appropriately leveraging context from both the environment and the user behaviours when designing user-in-the-loop systems.

Despite differences in training protocols, ensuring a fair comparison across all models was a key goal of the experimental design. Each model received 300 seconds of training data and the loss curves shown in Figure 3.4 indicate that training began to plateau by 150 epochs for the SGT models. Therefore, we argue that all models were evaluated fairly in terms of data, training, and user burden. Although training loss decreased for all models during initial training, it increased for both adaptive models

during the adaptation phase. In contrast, Figure 3.5 shows that throughput steadily increased throughout the adaptation phase, confirming that the incremental learning employed in this work resulted in better models. This is consistent with previous work [29] implementing CIIL, where it was found that optimizing for online performance can degrade offline performance. In addition to data considerations (e.g. the inclusion of more variable training data during the adaptation process), it is possible that some of the benefits seen with the adaptive models could be associated with user learning. While this is a valid consideration, Figure 3.5 demonstrates that all models showed a similar increase in throughput over the validation phase, indicating that the large benefits seen during adaptation —and, by extension, validation—are primarily driven by incremental learning rather than pure user learning. Overall, the results of this work suggest that the benefits of incremental learning far outweigh those of increasing SGT data or simply allowing the user more time to learn the system.

Despite both proving beneficial, the results of this work demonstrate clear differences between the two adaptive approaches. The average throughputs between the adaptive approaches were very similar, but the other usability metrics show the benefits of more appropriately considering user compliance in T-CIIL. T-CIIL outperformed O-CIIL in path efficiency, overshoots, completion rate, action interference, drift, and simultaneity gain. Furthermore, T-CIIL significantly improved many of these metrics compared to the non-adaptive SGT models, whereas O-CIIL did not always. Specifically, it’s worth noting that the action interference was significantly better for T-CIIL than O-CIIL, confirming the notion discussed in the introduction that assuming that the user always goes directly to the target contributes to action interference. Figure 3.6 shows that O-CIIL had far greater % simultaneity than T-CIIL, but T-CIIL had better path efficiency and simultaneity gain, furthering the point that O-CIIL provides at least some degree of uncontrollable simultaneity. Smith et

al. [69] have highlighted the importance of isolated motions for simultaneous control systems, specifically for finer movements. T-CIIL has improved on these problem areas compared to O-CIIL, confirming that the tweaks made to the pseudo-label decision flow are beneficial. Figure 3.4 corroborates this by showing that the loss increased more throughout the adaptation phase for O-CIIL than T-CIIL, suggesting that the labels provided by O-CIIL, which assumes you’re always going to the target, have a higher entropy than those provided by T-CIIL. Along with contributing to action interference, the incorrect labels produced by O-CIIL during inactive periods mislabel these periods as high-magnitude predictions, explaining why O-CIIL has higher drift than T-CIIL. Despite these limitations, both adaptive models reduce drift compared to the non-adaptive models, with T-CIIL showing a significant reduction. Overall, the improved action interference, simultaneity gain, and drift of T-CIIL shows that the modifications made to T-CIIL helped improve the control of both isolated and simultaneous motions at high and low amplitudes, demonstrating the benefit of leveraging task-specific context when training user-in-the-loop systems.

Although T-CIIL raised both the upper and lower bounds of performance, its average throughput was slightly lower than that of O-CIIL. Most other metrics clearly suggest that T-CIIL should have yielded better control, suggesting that this was influenced by some other factor. Interestingly, once a strong machine learning model has been established, throughput is largely determined by cursor speed, whereas the other usability metrics reward movement in the correct direction over speed [16, 29]. The survey results shown in Figure 3.7 also suggest that participants often preferred the control of T-CIIL over O-CIIL, but the speed of the cursor was better for O-CIIL. Based on these two results, it is likely that T-CIIL suffered from an issue with the speed mapping. Some parameters for T-CIIL, such as the mapping from cursor distance to proportional control magnitude (see Equation 3.1) and handling the activation threshold when creating pseudo-labels, were determined based on brief

piloting. These parameters are almost certainly not ideal for all users though. For example, if the activation threshold was too high for some participants, T-CIIL may not collect data until the participant is at 30% contraction strength, which could harm the speed mapping as it misses out on the low end of proportional control. The low end of proportional control has been shown to be crucial to online performance [15, 29], so any issue with the activation threshold could drastically impact usability. It is difficult to know the root cause of this without further investigation, though, so future work will explore how to determine a speed mapping or activation threshold that is robust for all users, such as through an adaptive approach similar to one employed in a previous implementation of CIIL [29]. Despite these limitations, participants clearly preferred the adaptive models over non-adaptive models, both in terms of the control and the training process. It was noted empirically that the benefits of T-CIIL were greater for novice users, likely due to their increased propensity for compliance issues. This bodes well for the ability of T-CIIL to generalize to persons with limb differences who may not have the same level of proprioception and/or who may calibrate more frequently with reduced attention. Overall, the improved performance of the adaptive CIIL models demonstrates the benefits of incremental learning for myoelectric control, and the differences between the two adaptive approaches highlight the impact user compliance issues can have on performance.

This work offers important insights into the use of simultaneity for regression-based myoelectric control. Truly independent, simultaneous, proportional control is arguably the greatest advantage of regression-based control schemes over classification, but this improved functionality can often become a burden due to undesired activations of other DoFs (i.e., action interference) [15–17, 34, 35]. One approach to improve the control of simultaneous motions has been to add simultaneous motions to the calibration data, but this has not always shown to be a benefit [26, 34]. For example, Smith et al. [34] suggested based on offline results that adding in combined

DoFs would harm performance for isolated motions, and the results in this work corroborate this through online experiments based on the significantly increased action interference of C-SGT compared to W-SGT. The results shown in Figure 3.3 demonstrate that adding combined motions to the training set slightly improved throughput and completion rate, but also provided a less robust model based on the inferior path efficiency, overshoots, action interference, drift, and simultaneity gain. In particular, the action interference and simultaneity gain exhibited the largest differences when adding combined motions to the calibration data. These metrics exhibited largely the same pattern, with W-SGT and T-CIIL significantly outperforming C-SGT and O-CIIL. Generally, adding combined motions to the training set increased the simultaneity used by each participant, but the subsequent degradation of action interference and simultaneity gain indicates that this simultaneity was often undesired and uncontrollable. Interestingly, simultaneity gain is slightly worse for O-CIIL than C-SGT despite O-CIIL having a better path efficiency and Figure 3.6 suggesting that the two models have similar simultaneity.

The results of this work also suggest that simply adding simultaneous motions to the calibration data may not provide a more robust controller, and, in this case, often did more harm than good. This is in contrast to the findings of Paskett et al. [26], who found that adding simultaneous motions to the calibration data helped overall performance, but only for certain models. Consequently, future work could continue to explore the role of the model in simultaneity and adaptation.

Chapter 4

Discussion

4.1 Overview

The work presented in this thesis highlights the complexity of training and evaluating regression-based myoelectric controllers and suggests that overcoming many related challenges may be achievable through a user-centered design. Motivated by inconsistencies in visual prompting styles used throughout the literature [16,18,19,27,34], the impact of the prompting style on user compliance was first investigated in Chapter 2. Figure 2.2 demonstrated two distinct user behaviours, namely *all or nothing* and *anticipation*, that were amplified by certain prompting styles. In response to this, a separate pilot study was performed to explore the effect of these behaviours on downstream usability. Figure 2.3 confirmed that participants correctly exaggerated the desired behaviours to investigate their impact in an extreme case. Finally, Figure 2.4 showed that the anticipation behaviour completely deteriorated the performance of the linear SVM, but not the RBF SVM. The results of this preliminary study primarily target Aim 1, demonstrating that the prompting style affects how the user follows the prompt and that these user behaviours can drastically impact usability

for some models.

Motivated by the results of Chapter 2, which further corroborated the difficulty of training regression-based myoelectric controllers, Chapter 3 explored an alternative training protocol altogether in the form of co-adaptation via CIIL. Four models were investigated in an online validation task: 1) W-SGT, a baseline SGT model training on within-DoF SGT data; 2) C-SGT, a baseline SGT model training on within-DoF and combined-DoF SGT data; 3) O-CIIL, a naive co-adaptive model that assumes that the user always travels along the optimal path; and 4) T-CIIL, a co-adaptive model that was modified to tolerate user behaviours and compliance issues. Figure 3.3 demonstrated that both adaptive models outperformed both non-adaptive models. Notably, O-CIIL significantly outperformed W-SGT in most metrics, and C-SGT in throughput, path efficiency, and trials. In contrast, T-CIIL significantly outperformed W-SGT in all metrics except action interference and simultaneity gain, and was significantly better than C-SGT in all metrics. W-SGT outperformed all other models in action interference and simultaneity gain, primarily due to a lack of simultaneity overall.

Figure 3.5 confirmed that both adaptive protocols improved effectively over the adaptation period. Although the adaptive models had similarities, the modifications made to T-CIIL improved performance for many metrics, significantly so for action interference and simultaneity gain. Despite the improved performance of T-CIIL, throughput was similar for both adaptive models, potentially due to an issue in the speed mapping for T-CIIL based on the subjective feedback shown in Figure 3.7. Nevertheless, participants still preferred the adaptive models overall both in terms of control and the training protocol. Notably, participants felt more in control of simultaneous motions with the adaptive models, corroborated by the action interference, simultaneity gain, and % simultaneity. Figures 3.3 and 3.6 clearly showed that simply adding simultaneous motions to the training set improved the amount of

simultaneity, but the subsequent control of this simultaneity was significantly worsened. Based on these results, T-CIIL provided the best balance by producing a controller with robust within-DoF performance, intentional combined-DoF performance, and a clear user preference over traditional SGT approaches.

The results of Chapter 3 primarily addressed Aims 2 and 3 of this thesis. Specifically, the superior performance of the adaptive approaches, both in the adaptation and validation phases, demonstrates that the user and model can co-adapt effectively when employing CIIL and the resultant models outperform models trained using traditional SGT. The differences between O-CIIL and T-CIIL, namely the improvement in the targeted robustness issues of action interference and drift, showcase the importance of incorporating realistic user-in-the-loop behaviours into model design for myoelectric controllers.

4.2 Contributions

First and foremost, the work presented in this thesis offers important insights into the impact of the training protocol on regression-based myoelectric controllers. Preliminary work demonstrated that the prompting style, a previously largely neglected factor in the training protocol, can magnify undesirable user behaviours. Emulating these behaviours then proved to impact usability for some models, showing that the effect of these behaviours is model-dependent. Interestingly, the all or nothing behaviour outperformed the baseline behaviour in some cases despite showing worse temporal alignment with the prompt. The all or nothing behaviour had very little focus on the middle range of the proportional control, which recent work [29] suggests is more accurate to how users control the device. Therefore, the results of this work suggest that training methods more similar to how users will use the device (i.e., motivated by user behaviours) may be more impactful than temporal

alignment. Consequently, the all or nothing behaviour resulted in more repeatable ramp up/down across repetitions, which may have also contributed to its superior performance.

Given the long list of interacting confounds involved with SGT, the second study was performed to investigate co-adaptive approaches using CIIL. Primarily, this work demonstrated for the first time that CIIL can effectively train a model via co-adaptation in an unconstrained, velocity-controlled goal-oriented environment for regression-based myoelectric control. The performance of the adaptive models compared to the SGT models confirms that CIIL is not only functional but also a significant improvement over conventional approaches. Contrasting the two adaptive models, T-CIIL outperformed O-CIIL on the targeted robustness issues. In particular, O-CIIL had significantly worse action interference and simultaneity gain, suggesting that the naive assumption (used in previous approaches [23,31]) that the user travels along the optimal path indeed contributes to action interference. Despite the improvement in critical robustness issues, however, the throughput of T-CIIL was similar to that of O-CIIL, highlighting the importance of the proportional control mapping and overall speed on throughput.

This work provides impactful insights into simultaneity and its potential downsides for myoelectric control in a broader context. Based on the results of Figure 3.3 and 3.6, % simultaneity does not always correlate with path efficiency, indicating that some of this simultaneity was either unintentional or uncontrollable. Unintentional activation of simultaneity and the benefits of additional simultaneity were quantified using two novel metrics: action interference and simultaneity gain, respectively. Paskett et al. [26] demonstrated the benefits of combined movements, but they looked at overall performance instead of focusing on action interference. Similar to Smith et al. [34], who demonstrated this effect offline, the results presented in this work confirm for the first time that it also holds online—showing that including simultaneous

motions in the training set may improve overall performance but harms within-DoF performance. Similarly, O-CIIL had a higher % simultaneity and enforced simultaneity more than T-CIIL based on expecting the user to travel along the optimal path. Despite O-CIIL having a higher % simultaneity, however, T-CIIL had a higher path efficiency. The improved simultaneity gain and action interference of T-CIIL suggest that users moved simultaneously when beneficial but were not forced to do so by the model, further confirming that designing co-adaptive protocols around specific issues reinforces desired model traits.

This work also presents observations about the differences between classification and regression in the broader context of machine learning. CIIL has shown promising performance in classification-based control [29,39,40], but this work is the first time it has been used for regression-based control. Determining the appropriate action in classification-based control has the benefit of a predefined number of potential actions (i.e., the number of classes). Previous implementations have determined the correct action based on hard pseudo-labels and Euclidean distance [39,40] or using soft labels when the most likely action is uncertain [29], but these approaches do not work in regression-based control due to the continuous spectrum of potential actions. To avoid the complications of determining suitable actions, previous co-adaptive approaches in regression-based myoelectric control took the easiest, but naive, approach by assuming that the user acts optimally [23,31]. As shown in Figure 3.1, this work built on previous CIIL work [29,39,40] by sorting predictions into predefined quadrants, limiting the number of suitable actions to apply positive and negative context. The results of this work demonstrate that this approach successfully restricts the action space to a sensible set of potential actions, confirming that the underlying logic effectively reinforces the desired behaviours, as evidenced by the reduced action interference.

Along with the continuous action space, switching from classification to regression

also required new solutions to handling proportional control. Proportional control is separate from the model in classification-based control, requiring manually setting (and potentially adapting) proportional control boundaries [29]. Regression-based control, on the other hand, requires the model itself to learn the proportional control, indicating that this information must be gleaned from the environment when training via co-adaptation. Where others have used position control (which differs from the ultimate use case) or constrained environments to acquire this information [23, 31, 32, 38, 71], this work employed a distance to proportional control mapping to acquire proportional control information from an unconstrained velocity-controlled environment (see Equation 3.1). Given the success of the co-adaptive models in this work, our findings indicate that proportional control information can be acquired from an online environment and used to train high-performing models.

4.3 Limitations and Future Work

The results presented in this thesis provide important considerations for training regression-based myoelectric control systems, but they are not without their limitations. As previously discussed, the preliminary study described in Chapter 2 is limited by the small sample size. With only 3 subjects for each model, not enough participants were recruited to make significant claims. It was for this reason that no statistical testing was done in that study, and the interpretation of the results considered that this was preliminary work aimed at exploring the complex interaction between users, the prompting style, and the model. Furthermore, the user behaviours during the online portion of the study were purposely exaggerated, so the effect size in real-world use would be much smaller. While this was deemed necessary to overcome the small sample size, it once again limits the generalizability of these results. Despite the limited sample size, this was deemed acceptable in the context

of this work as an early pilot to inform training for future in-depth exploration. Despite being exploratory, the trends were consistent enough across participants and with previous research to motivate the remainder of the work in this thesis. In particular, the effect of each behaviour on performance and the fact that these effects were model-dependent reinforced the complex and undesirable interactions introduced during SGT. This suggested that an alternative training paradigm may be needed to meaningfully improve regression-based myoelectric control, thus motivating the work presented in Chapter 3. Furthermore, now that these behaviours have been identified, future work can be performed investigating why these behaviours occur, what their real-world effect may be in the presence of more realistic data (i.e., not exaggerated), and if they may be mitigated in traditional SGT.

Unlike Chapter 2, whose goal was more exploratory, Chapter 3 provided a more in-depth investigation into multiple training protocols and their effect on usability. This enabled a more rigorous statistical analysis that demonstrated significant effects across many metrics. Although the number of participants was deemed to be sufficient based on conventions in the field, it is worth noting that the sample size is still somewhat limited. The primary limitation in terms of population for both Chapters 2 and 3, however, is the lack of representation of individuals with limb differences. While no firm claims can be made about whether this approach will generalize to persons with limb differences it is conceivable that the benefits of the personalized, co-adaptive approach CIIL may actually be stronger for persons with reduced visual and proprioceptive feedback [74, 75]. Although it has been widely adopted in EMG research, all online validation in this thesis was done in a virtual Fitts' Law style task [1], which lacks multiple real-world factors of prosthesis use such as the weight and physics of a device. Demonstrating these findings on users with a physical prosthesis performing functional tasks would be more representative of real-world use. Although their inclusion would be ideal, time constraints and availability limited

the inclusion of persons with a limb difference and the use of a physical device in this experimental design. Despite these experimental design constraints, the work presented in this thesis demonstrated the viability of this approach, an important first step that motivates future work into the application of CIIL to persons with limb differences, its deployment on a physical device, and the combination of these two factors. While CIIL has yet to be validated on a physical device, it has been shown to recover and perform well after electrode shift, a critical confound in real-world prosthetics use, which bodes well for its generalization to real-world use [39]. In addition to the challenges of incorporating a physical device in an experiment, its use also raises questions about acquiring context from a real-world environment. Chou et al. [31] have demonstrated that using eye tracking as context to create pseudo-labels produces performance on-par with that of using the target location as the source of truth, as was done in this thesis. In theory, using eye tracking to create pseudo-labels would be possible in the CIIL framework demonstrated in this work, but further investigation is needed to determine the viability of this approach. Furthermore, whether this level of context is required or beneficial for continued long-term CIIL in real-world use remains an open area of investigation.

Nevertheless, based on the results of this work, both CIIL approaches significantly improved multiple crucial facets of myoelectric control. In particular, T-CIIL demonstrated superior performance and resilience to imperfect user behaviours, even compared to O-CIIL. Despite these benefits, CIIL still requires some tuning. The obvious first step from this work is the issue with the speed mapping of T-CIIL, as shown in Figure 3.7. Tully et al. [27] have demonstrated the importance of spatial alignment (i.e., aligned magnitudes between the user’s action and the output) in training effective controllers. This explains why O-CIIL and T-CIIL had similar throughput, a metric primarily determined by speed [16, 29], despite T-CIIL outperforming O-CIIL in other control metrics. One potential cause of the poor speed mapping

for T-CIIL is the employed distance to proportional control equation (see Equation 3.1). Multiple mappings were piloted when developing the CIIL approaches in this work, but an in-depth comparison of performances using different mappings was not performed. Equation 3.1 was primarily motivated by previous CIIL work [29] demonstrating that users primarily move either fast or slow, but a better mapping likely exists. Nonetheless, it is worth noting that the results of this work show the promise of CIIL despite sub-optimal parameters, suggesting further improvements can be achieved through future research. In particular, this work motivates further investigation into more robust distance-to-proportional control mappings, ideally including mappings informed by user behaviours.

Given that no users reported an issue with the speed mapping for O-CIIL, however, the proportional control of T-CIIL was more likely affected by some aspect of the decision flow when creating pseudo-labels. Based on observations during the experiment, the most likely culprit is the logic for handling the activation threshold. Differentiating between periods of rest and active contraction based on EMG activity was piloted using multiple techniques, but on only a small set of participants, so it is not fully known how well the selected approach generalized to all users. Even still, it was challenging to find a threshold and technique that worked for all participants in the pilot study. Specifically, the low amplitude contractions of wrist rotation proved to be a challenge—a threshold that was too low was less resilient to user behaviours, but a threshold that was too high ignored intentional activations of wrist rotation. The instances of poor proportional control likely stemmed from the activation threshold being too high, so the user could not sufficiently control the low end of wrist rotation. This aligns with [27], demonstrating the importance of spatial alignment. Nevertheless, the goal of this work was primarily to demonstrate the viability of CIIL in a regression environment, and these results have highlighted both its promising performance and potential areas of improvement for future work.

In particular, a continuation of this work should explore multiple methods for differentiating between active and rest periods from the raw EMG signal, such as a moving average (used in this work), only considering a single window, or an adaptive approach that tailors to the participant throughout the adaptation phase (e.g., the Gaussian mixture model approach employed in [29]). Other work could investigate the best method to initialize the model used as a starting point for CIIL. All SGT data in this work followed the same protocol to provide a fair assessment of training protocols, but others have trained regression-based myoelectric controllers by simply collecting at the endpoints of each DoF [76]. Given the difficulty of accurately following a prompt [27] and the success of zero-shot training via CIIL in classification-based control [29], future work could investigate seeding CIIL with just data from the endpoints of each DoF.

The broader implications of simultaneity discussed in this work are limited by the complex interactions between the model architecture and many facets of myoelectric control. To be specific, the effect of including simultaneous motions in the training set is known to be model-specific [26], so some architectures may not exhibit the same effect shown by these results. For example, nonlinear models appear to benefit from the use of combined motions in the training set [26], whereas those that have argued that combined motions are unnecessary have tended to use linear models [19]. Nonetheless, CIIL has been shown to work with multiple architectures in previous work, ranging from simple linear classifiers to deep learning networks, and the results in this work show that it significantly outperformed the model-dependent approach of simply adding simultaneous motions to the training set [29, 39, 40]. Further work should however be done to investigate the effect that the architecture has on the proposed CIIL approach.

Finally, given recent evidence supporting mirror training [27] it could be adopted for both adaptive and non-adaptive approaches, although it is difficult to assess

whether its inclusion would help some protocols more than others. Similar to other CIIL parameters, these results motivate further investigation into the best method to seed CIIL, such as via mirror training [27]. More experimental approaches, such as using additive 1-DoF EMG [77] could also be investigated to improve simultaneity, but all of these investigations are limited by model effects. Overall, the results of this work successfully demonstrated the viability of CIIL in a regression-based environment, simultaneously highlighting promising performance and potential areas of future research.

In conclusion, the results of this work demonstrate the importance of the training protocol on regression-based myoelectric control. Aim 1 was investigated in Chapter 2, demonstrating that the prompting style can impact user compliance. Motivated by the confounds of SGT, CIIL was demonstrated to outperform traditional SGT approaches, satisfying Aim 2. Finally, multiple co-adaptive approaches were employed to explore Aim 3. Based on these results, modifying the co-adaptive protocol to target specific issues succeeds in minimizing these issues, providing important insights into training regression-based myoelectric controllers moving forward.

Bibliography

- [1] I. S. MacKenzie, “Fitts’ law,” *The Wiley Handbook of Human-Computer Interaction*, vol. 1, pp. 347–370, 2018.
- [2] E. Scheme and K. Englehart, “Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use.” *Journal of Rehabilitation Research & Development*, vol. 48, no. 6, 2011.
- [3] H. Huang, L. J. Hargrove, M. Ortiz-Catalan, and J. W. Sensinger, “Integrating upper-limb prostheses with the human body: Technology advances, readiness, and roles in human–prosthesis interaction,” *Annual Review of Biomedical Engineering*, vol. 26, 2024.
- [4] M. A. Oskoei and H. Hu, “Myoelectric control systems—a survey,” *Biomedical Signal Processing and Control*, vol. 2, no. 4, pp. 275–294, 2007.
- [5] E. Eddy, E. Campbell, A. Phinyomark, S. Bateman, and E. Scheme, “LibEMG: An Open Source Library to Facilitate the Exploration of Myoelectric Control,” *IEEE Access*, vol. 11, pp. 87 380–87 397, 2023.
- [6] A. Tabor, S. Bateman, and E. Scheme, “Evaluation of myoelectric control learning using multi-session game-based training,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 9, pp. 1680–1689, 2018.

- [7] C. labs at Reality Labs, D. Sussillo, P. Kaifosh, and T. Reardon, “A generic noninvasive neuromotor interface for human-computer interaction,” *bioRxiv*, pp. 2024–02, 2024.
- [8] V. Sivakumar, J. Seely, A. Du, S. R. Bittner, A. Berenzweig, A. Bolarinwa, A. Gramfort, and M. I. Mandel, “emg2qwerty: A large dataset with baselines for touch typing using surface electromyography,” in *Advances in Neural Information Processing Systems*, vol. 37, Vancouver, Canada, December 2024, pp. 91 373–91 389.
- [9] S. Salter, R. Warren, C. Schlager, A. Spurr, S. Han, R. Bhasin, Y. Cai, P. Walkington, A. Bolarinwa, R. Wang, N. Danielson, J. Merel, E. Pnevmatikakis, and J. Marshall, “emg2pose: A large and diverse benchmark for surface electromyographic hand pose estimation,” in *Advances in Neural Information Processing Systems*, vol. 37, Vancouver, Canada, December 2024, pp. 55 703–55 728.
- [10] E. Eddy, E. J. Scheme, and S. Bateman, “A framework and call to action for the future development of emg-based input in hci,” in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, Hamburg, Germany, April 2023, pp. 1–23.
- [11] E. Eddy, E. Campbell, S. Bateman, and E. Scheme, “On-demand myoelectric control using wake gestures to eliminate false activations during activities of daily living,” *arXiv preprint arXiv:2402.10050*, 2024.
- [12] S. P. Narayanan and A. E. Bharucha, “A practical guide to biofeedback therapy for pelvic floor disorders,” *Current Gastroenterology Reports*, vol. 21, pp. 1–8, 2019.
- [13] L. Criado, A. de La Fuente, M. Heredia, J. Montero, A. Albaladejo, and J.-M. Criado, “Electromyographic biofeedback training for reducing muscle pain and

- tension on masseter and temporal muscles: A pilot study,” *Journal of Clinical and Experimental Dentistry*, vol. 8, no. 5, p. e571, 2016.
- [14] A. D. Roche, H. Rehbaum, D. Farina, and O. C. Aszmann, “Prosthetic myoelectric control strategies: a clinical perspective,” *Current Surgery Reports*, vol. 2, pp. 1–11, 2014.
 - [15] A. Ameri, E. N. Kamavuako, E. J. Scheme, K. B. Englehart, and P. A. Parker, “Support vector regression for improved real-time, simultaneous myoelectric control,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 6, pp. 1198–1209, 2014.
 - [16] A. Ameri, M. A. Akhaee, E. Scheme, and K. Englehart, “Regression convolutional neural network for improved simultaneous emg control,” *Journal of Neural Engineering*, vol. 16, no. 3, p. 036015, 2019.
 - [17] M. Nowak, T. Eiband, E. R. Ramírez, and C. Castellini, “Action interference in simultaneous and proportional myocontrol: comparing force-and electromyography,” *Journal of Neural Engineering*, vol. 17, no. 2, p. 026011, 2020.
 - [18] J. M. Hahne, H. Rehbaum, F. Biessmann, F. C. Meinecke, K.-R. Müller, N. Jiang, D. Farina, and L. C. Parra, “Simultaneous and proportional control of 2d wrist movements with myoelectric signals,” in *2012 IEEE International Workshop on Machine Learning for Signal Processing*. Santander, Spain: IEEE, September 2012, pp. 1–6.
 - [19] J. M. Hahne, F. Biessmann, N. Jiang, H. Rehbaum, D. Farina, F. C. Meinecke, K.-R. Müller, and L. C. Parra, “Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 2, pp. 269–279, 2014.

- [20] A. Ameri, E. J. Scheme, E. N. Kamavuako, K. B. Englehart, and P. A. Parker, “Real-time, simultaneous myoelectric control using force and position-based training paradigms,” *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 2, pp. 279–287, 2013.
- [21] E. Scheme, B. Lock, L. Hargrove, W. Hill, U. Kuruganti, and K. Englehart, “Motion normalized proportional control for improved pattern recognition-based myoelectric control,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 1, pp. 149–157, 2013.
- [22] G. Hajian, E. Campbell, M. Ansari, E. Morin, A. Etemad, K. Englehart, and E. Scheme, “Generalizing upper limb force modeling with transfer learning: A multimodal approach using EMG and IMU for new users and conditions,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024.
- [23] J. M. Hahne, S. Dähne, H.-J. Hwang, K.-R. Müller, and L. C. Parra, “Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 4, pp. 618–627, 2015.
- [24] L. H. Smith, T. A. Kuiken, and L. J. Hargrove, “Use of probabilistic weights to enhance linear regression myoelectric control,” *Journal of Neural Engineering*, vol. 12, no. 6, p. 066030, 2015.
- [25] J. L. Nielsen, S. Holmgaard, N. Jiang, K. Englehart, D. Farina, and P. Parker, “Enhanced emg signal processing for simultaneous and proportional myoelectric control,” in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Minneapolis, USA: IEEE, September 2009, pp. 4335–4338.

- [26] M. D. Paskett, M. R. Brinton, T. C. Hansen, J. A. George, T. S. Davis, C. C. Duncan, and G. A. Clark, “Activities of daily living with bionic arm improved by combination training and latching filter in prosthesis control comparison,” *Journal of NeuroEngineering and Rehabilitation*, vol. 18, pp. 1–18, 2021.
- [27] T. N. Tully, C. J. Thomson, G. A. Clark, and J. A. George, “Validity and impact of methods for collecting training data for myoelectric prosthetic control algorithms,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024.
- [28] N. Fallentin, K. Jørgensen, and E. B. Simonsen, “Motor unit recruitment during prolonged isometric contractions,” *European Journal of Applied Physiology and Occupational Physiology*, vol. 67, pp. 335–341, 1993.
- [29] E. Campbell, E. Eddy, X. Isabel, S. Bateman, B. Gosselin, U. Côté-Allard, and E. Scheme, “Screen guided training does not capture goal-oriented behaviours: Learning myoelectric control mappings from scratch using context informed incremental learning,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, pp. 1–1, 2024.
- [30] E. J. Scheme and K. B. Englehart, “Validation of a selective ensemble-based classification scheme for myoelectric control using a three-dimensional fitts’ law test,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, no. 4, pp. 616–623, 2012.
- [31] A. H. Chou, M. Madduri, S. J. Li, J. Isa, A. Christensen, F. L. Hutchison, S. A. Burden, and A. L. Orsborn, “Using eye gaze to train an adaptive myoelectric interface,” *bioRxiv*, pp. 2024–04, 2024.
- [32] J. L. Betthausen, R. Greene, A. Dhawan, J. T. Krall, C. L. Hunt, G. Levay, R. R. Kaliki, M. S. Fifer, S. Sikdar, and N. V. Thakor, “Online adaptation for

- myographic control of natural dexterous hand and finger movements,” *arXiv preprint arXiv:2412.17991*, 2024.
- [33] D. Yeung, D. Farina, and I. Vujaklija, “Directional forgetting for stable co-adaptation in myoelectric control,” *Sensors*, vol. 19, no. 9, p. 2203, 2019.
 - [34] L. H. Smith, T. A. Kuiken, and L. J. Hargrove, “Evaluation of linear regression simultaneous myoelectric control using intramuscular emg,” *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 4, pp. 737–746, 2015.
 - [35] J. Li, Z. Zhu, W. J. Boyd, C. Martinez-Luna, C. Dai, H. Wang, H. Wang, X. Huang, T. R. Farrell, and E. A. Clancy, “Virtual regression-based myoelectric hand-wrist prosthesis control and electrode site selection using no force feedback,” *Biomedical Signal Processing and Control*, vol. 82, p. 104602, 2023.
 - [36] Z. Zhu, J. Li, W. J. Boyd, C. Martinez-Luna, C. Dai, H. Wang, H. Wang, X. Huang, T. R. Farrell, and E. A. Clancy, “Myoelectric control performance of two degree of freedom hand-wrist prosthesis by able-bodied and limb-absent subjects,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 893–904, 2022.
 - [37] A. T. Wang, C. D. Olsen, W. C. Hamrick, and J. A. George, “Correcting temporal inaccuracies in labeled training data for electromyographic control algorithms,” in *2023 International Conference on Rehabilitation Robotics (ICORR)*. Singapore, Singapore: IEEE, September 2023, pp. 1–6.
 - [38] C. Igual and J. Igual, “Simultaneous three-degrees-of-freedom prosthetic control based on linear regression and closed-loop training protocol,” *Sensors*, vol. 24, no. 10, p. 3101, 2024.
 - [39] E. Campbell, E. Eddy, S. Bateman, U. Côté-Allard, and E. Scheme, “Context-informed incremental learning improves both the performance and resilience of

- myoelectric control,” *Journal of NeuroEngineering and Rehabilitation*, vol. 21, no. 1, p. 70, 2024.
- [40] E. Eddy, E. Campbell, S. Bateman, and E. Scheme, “Leveraging task-specific context to improve unsupervised adaptation for myoelectric control,” in *2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Honolulu, USA, October 2023, pp. 4661–4666.
- [41] K. Englehart and B. Hudgins, “A robust, real-time control scheme for multi-function myoelectric control,” *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848–854, 2003.
- [42] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. A. A. Bakar, K. Chellappan, and T. G. Chang, “Surface electromyography signal processing and classification techniques,” *Sensors*, vol. 13, no. 9, pp. 12 431–12 466, 2013.
- [43] L. H. Smith, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “Determining the optimal window length for pattern recognition-based myoelectric control: balancing the competing effects of classification error and controller delay,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 19, no. 2, pp. 186–192, 2010.
- [44] J. M. Hahne, M. A. Schweisfurth, M. Koppe, and D. Farina, “Simultaneous control of multiple functions of bionic hand prostheses: Performance and robustness in end users,” *Science Robotics*, vol. 3, no. 19, p. eaat3630, 2018.
- [45] S. Amsuess, I. Vujaklija, P. Goebel, A. D. Roche, B. Graimann, O. C. Aszmann, and D. Farina, “Context-dependent upper limb prosthesis control for natural and robust use,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 7, pp. 744–753, 2015.

- [46] O. C. Aszmann, I. Vujaklija, A. D. Roche, S. Salminger, M. Herceg, A. Sturma, L. A. Hruby, A. Pittermann, C. Hofer, S. Amsuess *et al.*, “Elective amputation and bionic substitution restore functional hand use after critical soft tissue injuries,” *Scientific Reports*, vol. 6, no. 1, p. 34960, 2016.
- [47] H. E. Williams, A. W. Shehata, K. Y. Cheng, J. S. Hebert, and P. M. Pilarski, “Myoelectric prosthesis control using recurrent convolutional neural network regression mitigates the limb position effect,” *bioRxiv*, pp. 2024–02, 2024.
- [48] J. L. Nielsen, S. Holmgaard, N. Jiang, K. B. Englehart, D. Farina, and P. A. Parker, “Simultaneous and proportional force estimation for multifunction myoelectric prostheses using mirrored bilateral training,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 3, pp. 681–688, 2010.
- [49] T. Tully, C. Thomson, G. Clark, and J. George, “User-specific mirror training can improve myoelectric prosthesis control,” in *Myoelectric Controls Symposium*, Fredericton, Canada, August 2022.
- [50] D. Di Domenico, I. Forsiuk, S. Müller-Cleve, S. Tanzarella, F. Garro, A. Marinelli, M. Canepa, M. Laffranchi, M. Chiappalone, C. Bartolozzi *et al.*, “Reach&grasp: a multimodal dataset of the whole upper-limb during simple and complex movements,” *Scientific Data*, vol. 12, no. 1, p. 233, 2025.
- [51] X. Jiang, X. Liu, J. Fan, X. Ye, C. Dai, E. A. Clancy, M. Akay, and W. Chen, “Open access dataset, toolbox and benchmark processing results of high-density surface electromyogram recordings,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1035–1046, 2021.
- [52] A. Krasoulis, S. Vijayakumar, and K. Nazarpour, “Effect of user practice on prosthetic finger control with an intuitive myoelectric decoder,” *Frontiers in Neuroscience*, vol. 13, p. 891, 2019.

- [53] N. M. Bhiri, S. Ameur, I. Alouani, M. A. Mahjoub, and A. B. Khalifa, “Hand gesture recognition with focus on leap motion: An overview, real world challenges and future directions,” *Expert Systems with Applications*, vol. 226, p. 120125, 2023.
- [54] J. Fan and X. Hu, “Decomposing task-relevant information from surface electromyogram for user-generic dexterous finger force decoding,” *IEEE Journal of Biomedical and Health Informatics*, 2024.
- [55] A. Hagengruber, U. Leipscher, B. M. Eskofier, and J. Vogel, “A new labeling approach for proportional electromyographic control,” *Sensors*, vol. 22, no. 4, p. 1368, 2022.
- [56] J. A. George, M. R. Brinton, C. C. Duncan, D. T. Hutchinson, and G. A. Clark, “Improved training paradigms and motor-decode algorithms: results from intact individuals and a recent transradial amputee with prior complex regional pain syndrome,” in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Honolulu, USA: IEEE, July 2018, pp. 3782–3787.
- [57] A. W. Shehata, E. J. Scheme, and J. W. Sensinger, “Evaluating internal model strength and performance of myoelectric prosthesis control strategies,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 5, pp. 1046–1055, 2018.
- [58] C. Morrell, E. Campbell, and E. Scheme, “Exploring user compliance in the training of regression-based myoelectric control,” in *Myoelectric Controls Symposium*, Fredericton, Canada, August 2024.
- [59] F. Chamberland, É. Buteau, S. Tam, E. Campbell, A. Mortazavi, E. Scheme, P. Fortier, M. Boukadoum, A. Campeau-Lecours, and B. Gosselin, “Novel wear-

- able hd-emg sensor with shift-robust gesture recognition using deep learning,” *IEEE Transactions on Biomedical Circuits and Systems*, 2023.
- [60] B. Hudgins, P. Parker, and R. N. Scott, “A new strategy for multifunction myoelectric control,” *IEEE Transactions on Biomedical Engineering*, vol. 40, no. 1, pp. 82–94, 1993.
- [61] M. Barsotti, S. Dupan, I. Vujaklija, S. Došen, A. Frisoli, and D. Farina, “Online finger control using high-density emg and minimal training data for robotic applications,” *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 217–223, 2018.
- [62] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “The target achievement control test: Evaluating real-time myoelectric pattern recognition control of a multifunctional upper-limb prosthesis,” *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, p. 619, 2011.
- [63] D. J. Atkins, D. C. Heard, and W. H. Donovan, “Epidemiologic overview of individuals with upper-limb loss and their reported research priorities,” *JPO: Journal of Prosthetics and Orthotics*, vol. 8, no. 1, pp. 2–11, 1996.
- [64] L. Schmalfuss, J. Hahne, D. Farina, M. Hewitt, A. Kogut, W. Doneit, M. Reichl, R. Rupp, and D. Liebetanz, “A hybrid auricular control system: direct, simultaneous, and proportional myoelectric control of two degrees of freedom in prosthetic hands,” *Journal of Neural Engineering*, vol. 15, no. 5, p. 056028, 2018.
- [65] A. J. Young, L. H. Smith, E. J. Rouse, and L. J. Hargrove, “A new hierarchical approach for simultaneous control of multi-joint powered prostheses,” in *2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, Rome, Italy, June 2012, pp. 514–520.

- [66] A. J. Young, L. H. Smith, E. J. Rouse, and L. Hargrove, “A comparison of the real-time controllability of pattern recognition to conventional myoelectric control for discrete and simultaneous movements,” *Journal of Neuroengineering and Rehabilitation*, vol. 11, pp. 1–10, 2014.
- [67] A. Phinyomark, E. Campbell, and E. Scheme, “Surface electromyography (emg) signal processing, classification, and practical considerations,” *Biomedical Signal Processing: Advances in Theory, Algorithms and Applications*, pp. 3–29, 2020.
- [68] E. Campbell, A. Phinyomark, and E. Scheme, “Deep cross-user models reduce the training burden in myoelectric control,” *Frontiers in Neuroscience*, vol. 15, p. 657958, 2021.
- [69] L. H. Smith, T. A. Kuiken, and L. J. Hargrove, “Myoelectric control system and task-specific characteristics affect voluntary use of simultaneous control,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 1, pp. 109–116, 2015.
- [70] C. Igual, J. Igual, J. M. Hahne, and L. C. Parra, “Adaptive auto-regressive proportional myoelectric control,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 2, pp. 314–322, 2019.
- [71] C. Igual, A. Castillo, and J. Igual, “An interactive training model for myoelectric regression control based on human–machine cooperative performance,” *Computers*, vol. 13, no. 1, p. 29, 2024.
- [72] D. Yeung, I. M. Guerra, I. Barner-Rasmussen, E. Siponen, D. Farina, and I. Vujaklija, “Co-adaptive control of bionic limbs via unsupervised adaptation of muscle synergies,” *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 8, pp. 2581–2592, 2022.

- [73] R. N. Khushaba, S. Kodagoda, S. Lal, and G. Dissanayake, “Driver drowsiness classification using fuzzy wavelet-packet-based feature-extraction algorithm,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 1, pp. 121–131, 2010.
- [74] E. Campbell, A. Phinyomark, A. H. Al-Timemy, R. N. Khushaba, G. Petri, and E. Scheme, “Differences in emg feature space between able-bodied and amputee subjects for myoelectric control,” in *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, San Francisco, USA, March 2019, pp. 33–36.
- [75] E. Campbell, J. Chang, A. Phinyomark, and E. Scheme, “A comparison of amputee and able-bodied inter-subject variability in myoelectric control,” in *Myoelectric Controls Symposium*, Fredericton, Canada, August 2020.
- [76] A. E. Olsson, N. Malešević, A. Björkman, and C. Antfolk, “Learning regularized representations of categorically labelled surface emg enables simultaneous and proportional myoelectric control,” *Journal of NeuroEngineering and Rehabilitation*, vol. 18, pp. 1–19, 2021.
- [77] Y. Yuan, C. Dai, J. Fan, C. Chou, J. Liu, and X. Jiang, “Training explainable and effective multi-dof emg decoder using additive 1-dof emg,” *IEEE Transactions on Medical Robotics and Bionics*, 2024.

Vita

Candidate's full name: Christian Bailey Morrell

Universities Attended:

2022 - Present	Master of Science in (Electrical) Engineering, University of New Brunswick
2018 - 2022	Bachelor of Science in (Electrical) Engineering, University of New Brunswick

Submissions:

1. C. Morrell, E. Campbell, E. Eddy, and E. Scheme, "Context-Informed Incremental Learning Improves Throughput and Reduces Drift in Regression-Based Myoelectric Control," *Transactions on Neural Systems and Rehabilitation Engineering* (Under Review), 2025

Publications:

1. C. J. Thomson et al., "Enhancing neuroprosthesis calibration: the advantage of integrating prior training over exclusive use of new data," *J. Neural Eng.*, vol. 21, no. 6, p. 066020, Nov. 2024, doi: 10.1088/1741-2552/ad94a7

2. C. Morrell, E. Campbell, and E. Scheme, “Exploring user compliance in the training of regression-based myoelectric control,” *Myoelectric Controls Symposium*, Aug. 2024, doi: 10.57922/mec.2507
3. R. P. Cusack et al., “Machine learning enabled detection of COVID-19 pneumonia using exhaled breath analysis: a proof-of-concept study,” *J. Breath Research*, vol. 18, no. 2, p. 026009, Mar. 2024, doi: 10.1088/1752-7163/ad2b6e
4. F. Naz et al., “Impact of breast density on classification of infrared spectroscopy for breath-based breast cancer screening,” *American Society of Clinical Oncology Annual Meeting*, 8, vol. 41, no. 16_suppl, pp. e13558–e13558, May 2023, doi: 10.1200/JCO.2023.41.16_SUPPL.E13558

Conference Presentations:

1. C. Morrell, J. Aikens, G. Beydaghyan, C. Purves, A. Fazeli, and E. Scheme, “Exploring Breath Profile Variability to Enable Early Disease Detection.” *Health Research Symposium*, Moncton, NB, Canada, 2024.
2. E. Eddy, E. Campbell, C. Morrell, and E. Scheme, “LibEMG: A New Open Source Library for Developing Myoelectric Interfaces and Conducting Myoelectric Control Research.” *Myoelectric Controls Symposium, Workshop*, Fredericton, NB, Canada, 2024.
3. C. Morrell, E. Campbell, and E. Scheme, “Exploring User Compliance in the Training of Regression-Based Myoelectric Control.” *Myoelectric Controls Symposium*, Fredericton, NB, Canada, 2024.
4. C. Morrell et al., “Machine Learning-Enabled Cavity Ring-Down Spectroscopy for the Detection of Non-small Cell Lung Cancer.” *New Brunswick Health Research Week*, Fredericton, NB, Canada, 2022.